Advancing methods and detecting meaningful change in coordination variability measures used in sports biomechanics

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Holly Abigail Stock

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Declaration of any previous submission of the work

The material presented here for examination for the award of a higher degree by research has not been incorporated into a submission for another degree.

Declaration of authorship

I am the author of this thesis, and the work described herein was carried out by myself personally.

ABSTRACT

Coordination variability measures have become popular within sports biomechanics for studying topics such as learning, expertise and injury. Research in these areas has suggested that coordination variability can enhance learning, be characteristic of expert skill levels and that excessively high or low variability may be a risk factor for injury.

Coordination variability measures in kinematic analyses have now been in use for over twenty years in sports biomechanics literature. A subset of kinematic coordination variability measures calculates the variability of vectors (which are formed between consecutive data points on an angle – angle diagram) and has therefore been termed 'vector coding'. This programme of research investigates two methodological considerations associated with vector coding variability measures. First, a combined simulated and experimental approach demonstrates a statistical artefact stemming from the use of circular statistics that can cause steep increases in coordination variability at times when very little movement occurs in the joints or segments, between which coordination is being measured. An alternative method for measuring coordination variability based on the calculation of ellipse areas is presented that is shown not to be affected by the artefact. Second, a further modification to the ellipse area method is proposed that uses angular velocities to represent angular dynamics. This contrasts with traditional vector coding techniques that use the change in angle between consecutive normalised time points. The use of angular velocities is suggested to align the vector coding methods with biomechanical conventions and retain more temporal information compared to the traditional method.

Very little research has detailed the repeatability of coordination variability measures and what magnitude of change might be methodologically or clinically meaningful. This programme of research therefore also investigates the repeatability of the ellipse area, angular velocity-based measure of coordination variability (the velocity ellipse method) proposed in the thesis. Two repeatability studies (of running gait and a 45 degree cutting movement) provided data to calculate what magnitude of change is methodologically meaningful for the velocity ellipse method. Experimental data is also presented, investigating scenarios where differences in coordination variability might be expected to occur. Specifically 1) in an individual who transitioned from a healthy state to one where running was painful and 2) between a population of individuals who had had an ACL reconstruction compared to a healthy population performing a 45 degree cutting manoeuvre before and after an acute fatigue intervention. Minimum detectable changes estimated from the repeatability data aided the interpretation of the experimental data. No differences were observed that were greater than the minimum

detectable changes in 1) the case study participant from data collections where they were pain free to one where running was painful, 2) cutting manoeuvres before and after a fatiguing protocol or 3) coordination variability between athletes who had had ACL reconstructions compared to a healthy control group. This could either suggest that the repeatability of the measure is too low to be able to detect clinically meaningful changes, or that injury and fatigue may not consistently induce meaningful changes in coordination variability measures. Limitations of the velocity ellipse method are discussed, and suggestions are made that may increase the repeatability and thus improve its ability to detect clinically meaningful differences in future research studies.

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CHAPTER 1: INTRODUCTION

1.1 Research Overview

Variability is an unavoidable characteristic of movement. The benefits of consistent outcomes in sport has led many to believe that variability in the movements that precede sporting outcomes such as shooting at a target, scoring a free shot in basketball, or a serve in tennis are undesirable. However, research has been published that counters this belief (e.g. Arutyunyan, Gurfinkel and Mirskii, 1969; C. Button et al., 2003; Whiteside et al., 2015) and authors have highlighted a number of areas in which variability can be functional (i.e. of practical use) in movement and the coordination of movement (Hamill et al., 1999; Bartlett, Wheat and Robins, 2007; Preatoni et al., 2013).

Variability has therefore itself become a focus of attention. Authors have explored many different techniques for measuring variability. Some techniques investigate the variability of single parameters, and others focus on the interaction between different movements and are consequently named coordination variability measures. The coordination variability approach has been advocated because human movement is the result of the coordinated actions of multiple body components. Body segments are connected to one another via joints and movements at one segment or joint impact those adjacent to them. Measures of coordination variability were first proposed over 35 years ago (e.g. Kelso, 1984) but the initial examples of coordination variability measures in the area of sports biomechanics appeared in the 90s (e.g. Diedrich and Warren, 1995). A seminal paper in 1999 found evidence for an association between coordination variability and injury, identifying lower coordination variability in a group of participants with patellofemoral pain than in healthy controls (Hamill et al., 1999). The authors suggested that measuring coordination variability could be useful for the detection and treatment of running injuries and hypothesised that low variability could be a contributing factor to injury. Sustaining sports injuries is known to have negative effects on the wellbeing of the individual (e.g. Hagger et al., 2005; Lohmander et al., 2007) and carries a financial cost due to treatment or working time lost (van Mechelen, 1997). Thus, since Hamill et al. (1999) was published, various authors have sought to quantify the relationship between coordination variability and injury but the majority of this research has been cross-sectional. Several authors have highlighted that more prospective measures and longitudinal tracking are needed to understand whether differences in coordination variability can be observed prior to injury, as well as after (e.g. Hamill et al., 1999; Bartlett, Wheat and Robins, 2007; Hamill, Palmer and van Emmerik, 2012; Baida et al., 2018). The body of work in this area is growing, documenting how coordination variability responds to different interventions (e.g. footwear

changes) or events (e.g. injury) but there has been little mention of how coordination variability might fluctuate when conditions remain largely unchanged, i.e. how repeatable measures of coordination variability are. Until the variation in coordination variability that can be expected under repeated conditions is well understood, it is not possible to understand whether changes observed between repeated measurements represent random fluctuations or meaningful change. The ability to distinguish between fluctuations and meaningful change is therefore also a prerequisite for understanding what magnitude of change is clinically meaningful, for example in relation to injury.

The lack of information on repeatability is pertinent for many of the coordination variability measures. The seminal paper in 1999 used a continuous relative phase technique for measuring coordination variability, but this technique has been suggested to be limited to sinusoidal data (Peters et al., 2003) so can only be used on very specific datasets. It has also been shown to produce different outputs according to the joint angle definition that is used (e.g. if the hip is defined as 0° or 180° when in a standing position (Mullineaux and Wheat, 2018)). Alternative methods were proposed in the 2000s (Hamill, McDermott and Haddad, 2000; Tepavac and Field-Fote, 2001; Heiderscheit, Hamill and van Emmerik, 2002) that have not been found to require sinusoidal time series inputs and can therefore be applied to a wider range of movement data. These methods are visualised using plots where two angles (segment or joint angles) are plotted against one another and the variability of vectors formed between consecutive data points on this plot is analysed. The methods have consequently been termed 'vector coding' techniques. These methods and their derivatives have continued to appear in the sports biomechanics literature for understanding whether differences in coordination variability exist between different populations (e.g. Heiderscheit, Hamill and van Emmerik, 2002; Wilson et al., 2008; Cunningham et al., 2014; Pollard et al., 2015; Whiteside et al., 2015; Raffalt, Alkjær and Simonsen, 2016; Boyer, Silvernail and Hamill, 2017; Takabayashi et al., 2018a; Harrison et al., 2019; Herb et al., 2020) and the effects of different interventions on the same individuals (e.g. Field-Fote and Tepavac, 2002; MacLean, van Emmerik and Hamill, 2010; Ferber and Pohl, 2011; Samaan et al., 2015b; Herb, Chinn and Hertel, 2016; Mudie et al., 2016; Hafer, Brown and Boyer, 2017; Takabayashi et al., 2018b; Floría et al., 2019; Jagodinsky et al., 2020; Weir et al., 2020). Due to their diverse applications and prevalence in the literature, coordination variability methods based on vector coding have been selected as the focus of this thesis, with particular emphasis and examples on their use within sports injury research to the lower limbs.

1.2 Research Aim

The aim of this doctoral research programme was to critically evaluate the use of vector coding variability methods and their relationship with injury.

1.3 Research Questions

Four specific objectives were targeted to address the overarching research aim that are summarised by the following questions:

1) Is the calculation of vector coding coordination variability valid?
2) How repeatable is velocity ellipse area coordination variability in commonly measured movements?
3) Do meaningful changes in coordination variability accompany injury in running?
4) Are meaningful changes in coordination variability observed between conditions such as fatigue or previous anterior cruciate ligament (ACL) injury, which are associated with increased risk of ACL injury in a cutting movement?

1.4 Organisation of chapters

Chapter 2 – Literature Review

The origins of interest in movement variability and its applications are discussed with particular emphasis on the evidence around movement variability and musculoskeletal lower limb injury. The evolution of coordination variability measures based on angle – angle plots is presented and is followed by a discussion of the validity, accuracy and repeatability of vector coding coordination variability measures. The chapter ends with a summary of what there is still to learn about vector coding coordination variability measures and their relevance to lower limb injury.

Chapter 3 – Applying circular statistics can cause artefacts in the calculation of vector coding variability: A bivariate solution

Circular statistics are frequently used in popular angle – angle plot derived coordination variability measures. One of the first papers to apply such measures warned of a potential measurement artefact related to the use of circular statistics (Heiderscheit, Hamill and van Emmerik, 2002). Chapter 3 therefore investigates the existence and effect of this artefact on simulated data and demonstrates the potential effects to experimental data. An alternative bivariate approach based on ellipse area calculations is proposed for measuring vector coding coordination variability that is shown not to be affected by the same artefact.

Chapter 4 – Angular dynamics in vector coding

The most popular methods of measuring coordination variability from angle – angle plots create vectors between consecutive points and analyse the direction or the direction and magnitude of these vectors to represent movement dynamics. Biomechanical conventions traditionally represent angular dynamics using angular velocities therefore this chapter explores the use of angular velocities as inputs to the coordination variability calculations in place of traditional inputs derived from calculating the change in angle between consecutive time points.

Chapter 5 – Repeatability and a longitudinal case study analysis of coordination variability in running gait

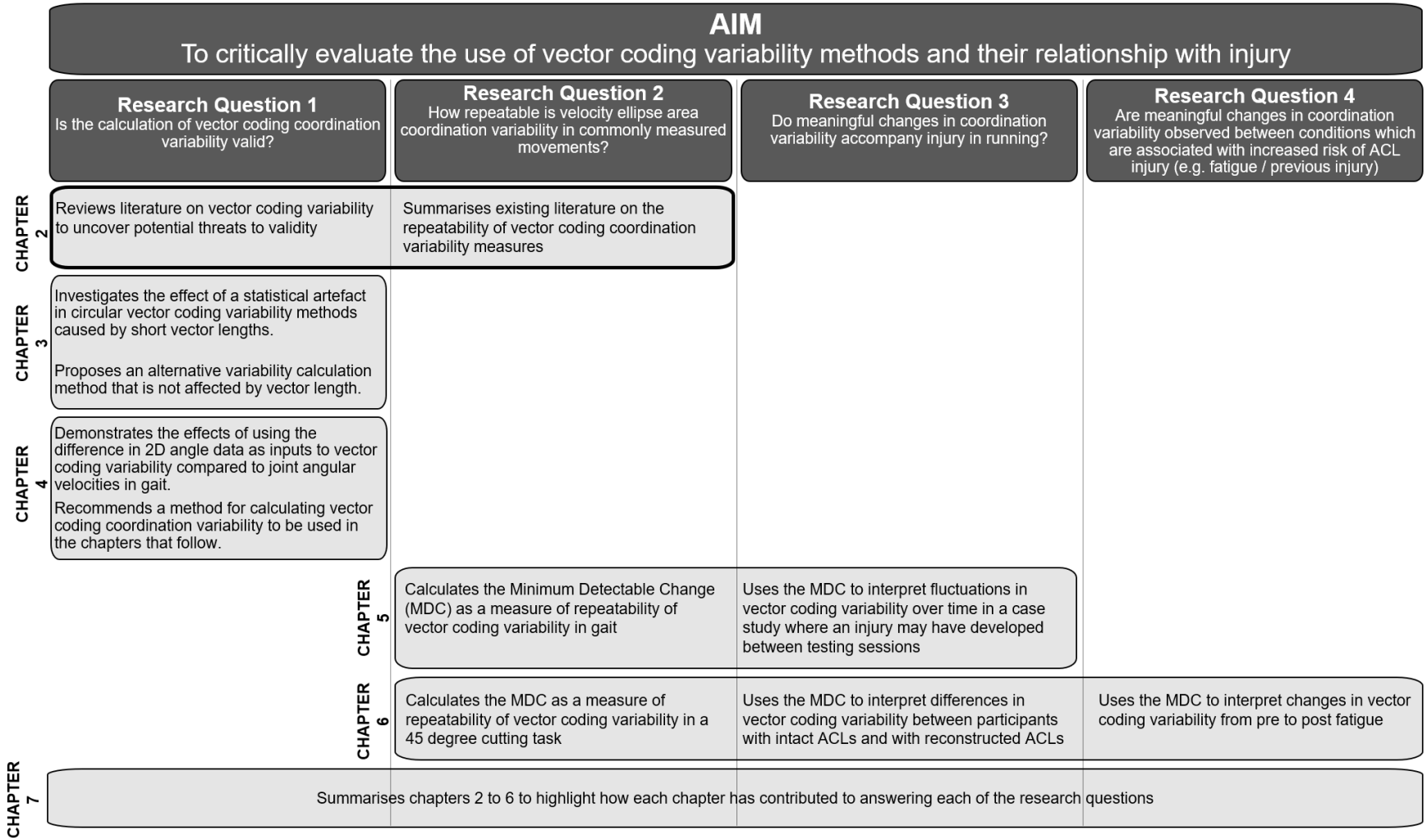
Running gait is the most commonly researched movement in relation to coordination variability and injury. Vector coding measures have frequently been applied to analyse this task but there have been no investigations that quantify the repeatability (absolute reliability) of coordination variability in running gait. Longitudinal tracking of coordination variability has been highlighted as a necessity in furthering our understanding of the relationship between coordination variability and injury and repeatability measures will be important in understanding within-individual changes over time. This chapter therefore takes multiple measurements of coordination variability during running gait over different time scales to estimate the within-day and between-day repeatability of coordination variability. These data are used to interpret whether coordination variability is linked to the onset of heel pain in one individual of the participant sample.

Chapter 6 –The repeatability and effect of fatigue and ACL injury on coordination variability in a cutting movement

Coordination variability has also been measured in cutting movements. The effects of fatigue, anticipation, gender and previous ACL injury have been investigated in the literature to better understand possible associations between coordination variability and ACL injury risk factors. The repeatability of coordination variability is not known in cutting movements but would benefit the interpretation of results quantifying the relationship between different ACL risk factors and coordination variability. Therefore, in Chapter 6 the results from two separate data collections are combined. In the first, two repeated measurements are collected to estimate the within-day repeatability of coordination variability in cutting. The second study investigates the effect of fatigue and previous ACL injury on coordination variability. The results of the repeatability analysis are used to provide additional context to any differences observed between groups or changes that occurred as a result of fatigue.

Chapter 7 – Discussion

Chapter 7 summarises the work conducted within this thesis to address how it has progressed knowledge in relation to each research question. The impact of these results is then outlined, followed by a discussion of methodological considerations that require further thought and investigation for future studies of coordination variability due to their possible influence on the coordination variability measure. Finally, more general recommendations for future research on coordination variability and sports injury are proposed.


AIM
To critically evaluate the use of vector coding variability methods and their relationship with injury
Research Question 1
Is the calculation of vector coding coordination variability valid?
Research Question 2
How repeatable is velocity ellipse area coordination variability in commonly measured movements?
Research Question 3
Do meaningful changes in coordination variability accompany injury in running?
Research Question 4
Are meaningful changes in coordination variability observed between conditions which are associated with increased risk of ACL injury (e.g. fatigue / previous injury)
CHAPTER 2
Reviews literature on vector coding variability to uncover potential threats to validity
Summarises existing literature on the repeatability of vector coding coordination variability measures
CHAPTER 3
Investigates the effect of a statistical artefact in circular vector coding variability methods caused by short vector lengths.
Proposes an alternative variability calculation method that is not affected by vector length.
CHAPTER 4
Demonstrates the effects of using the difference in 2D angle data as inputs to vector coding variability compared to joint angular velocities in gait.
Recommends a method for calculating vector coding coordination variability to be used in the chapters that follow.
CHAPTER 5
Calculates the Minimum Detectable Change (MDC) as a measure of repeatability of vector coding variability in gait
Uses the MDC to interpret fluctuations in vector coding variability over time in a case study where an injury may have developed between testing sessions
CHAPTER 6
Calculates the MDC as a measure of repeatability of vector coding variability in a 45 degree cutting task
Uses the MDC to interpret differences in vector coding variability between participants with intact ACLs and with reconstructed ACLs
Uses the MDC to interpret changes in vector coding variability from pre to post fatigue
CHAPTER 7
Summarises chapters 2 to 6 to highlight how each chapter has contributed to answering each of the research questions

CHAPTER 2: LITERATURE REVIEW

2.1 Variability

The human body is a mechanical system with many interacting components. Controlling these components to achieve a given task is a complex feat of coordination: there are very many coordinative solutions that would result in failure, but there are also numerous coordinative solutions that result in successful task achievement. This ability to achieve the same task outcome by activating different combinations of muscles in different ways is commonly referred to as redundancy (Bernstein, 1967) or abundancy (Latash, Scholz and Schöner, 2002) in movement control.

With the multitude of movement solutions available, the solutions selected when a single task is performed repeatedly are never identical and nor is the outcome: there is a degree of variability between them. Some of this variability is biological and occurs as a result of errors in: sensory processes, movement planning and movement execution (van Beers, Haggard and Wolpert, 2004), but changes to the environment and the accuracy of measurements can also contribute to the total variability that is detected (Preatoni et al., 2013). Variability in the way we perform movements has long been recognised, but biomechanics research has not always measured this variability due to the large amounts of time required to collect, process and analyse data for just one trial before advances in computing allowed many of these processes to be automated. As technology advanced and facilitated the collection, processing, analysis and storage of greater volumes of data it became common for researchers to collect multiple movement trials and report a measure of spread, normally a standard deviation, alongside. In a sporting context intrasubject measures of spread indicate to what extent the average is representative of the sample or the level of consistency or variability between repeated attempts. If the measure of spread value is very small this suggests that most samples are close to the average and that repetitions are highly consistent. When the difference between individual samples and the average increases, the measure of spread value will also increase and demonstrates greater variability between the repeated measurements. Because high consistency (i.e. low variability) of performance outcomes (also referred to as endpoint variability) is typically important in a sports context, variability in the movements that precede and generate the outcome (i.e. execution variability) was traditionally considered to indicate unwanted noise. The total variation (V_T) was believed to include biological variation (V_B) from sensory input and motor control output errors, environmental variation (V_E) from changing conditions and error that was the result of limitations in measurement (V_M) (Preatoni 2013, Equation 2.1)

$$V_T = V_B + V_E + V_M \quad (2.1)$$

Biological variation was traditionally regarded as random error and a negative feature of movement that the body minimises (e.g. Schmidt et al., 1979; Harris and Wolpert, 1998; van Beers, Baraduc and Wolpert, 2002) but in more recent years there has been greater recognition of the possible benefits of execution variability (e.g. Müller and Sternad, 2004; Bartlett, Wheat and Robins, 2007; Orth, Davids and Seifert, 2017). Some authors have specifically suggested that variability contains structure that makes it functional (i.e. of practical use) in human movement (Mandelblat-Cerf, Paz and Vaadia, 2009) and therefore should not be regarded simply as the product of errors in sensory input and motor output. Thus, different measures have emerged for measuring both the magnitude of execution variability and its structure. Analysis methods which fall within each of these categories have then explored the role of variability in themes such as motor learning, expert performance, health and disease and musculoskeletal injury.

A general summary of execution variability methods and their applications is provided below followed by a particular focus on the main topics of this thesis: 1) the measurement of coordination variability using vector coding and 2) the relationship between vector coding coordination variability and lower limb musculoskeletal injury.

2.1.1 Measures of Variability

Magnitude of variability

Multiple techniques have been used to quantify the total variability present across multiple repetitions of the same movement (i.e. execution variability) and these methods can be grouped into three categories: univariate, circular and multivariate. Many methods can be applied to discrete data at specific time points or events but can also be calculated for time series data by applying the same calculations independently to each temporal node. For time series analyses, the data is often temporally registered so that each movement repetition contains the same number of temporal nodes. Univariate measures of variability take a single variable and calculate the spread of data in this variable at each temporal node (e.g. Figure 2.1A & B). Spread is calculated using statistical methods such as the standard deviation and coefficient of variation (e.g. C. Brown et al., 2009; Nordin and Dufek, 2017; Paquette, Milner and Melcher, 2017). In contrast, circular methods create a coupling between two variables that are thought to have a meaningful interaction with one another. Circular statistics are used to calculate angular spread at each temporal node (e.g. Figure 2.1C to E) and are described as

measures of coordination variability as the variability measured is influenced by both variables in the coupling and the interaction between them. Examples of methods that include circular

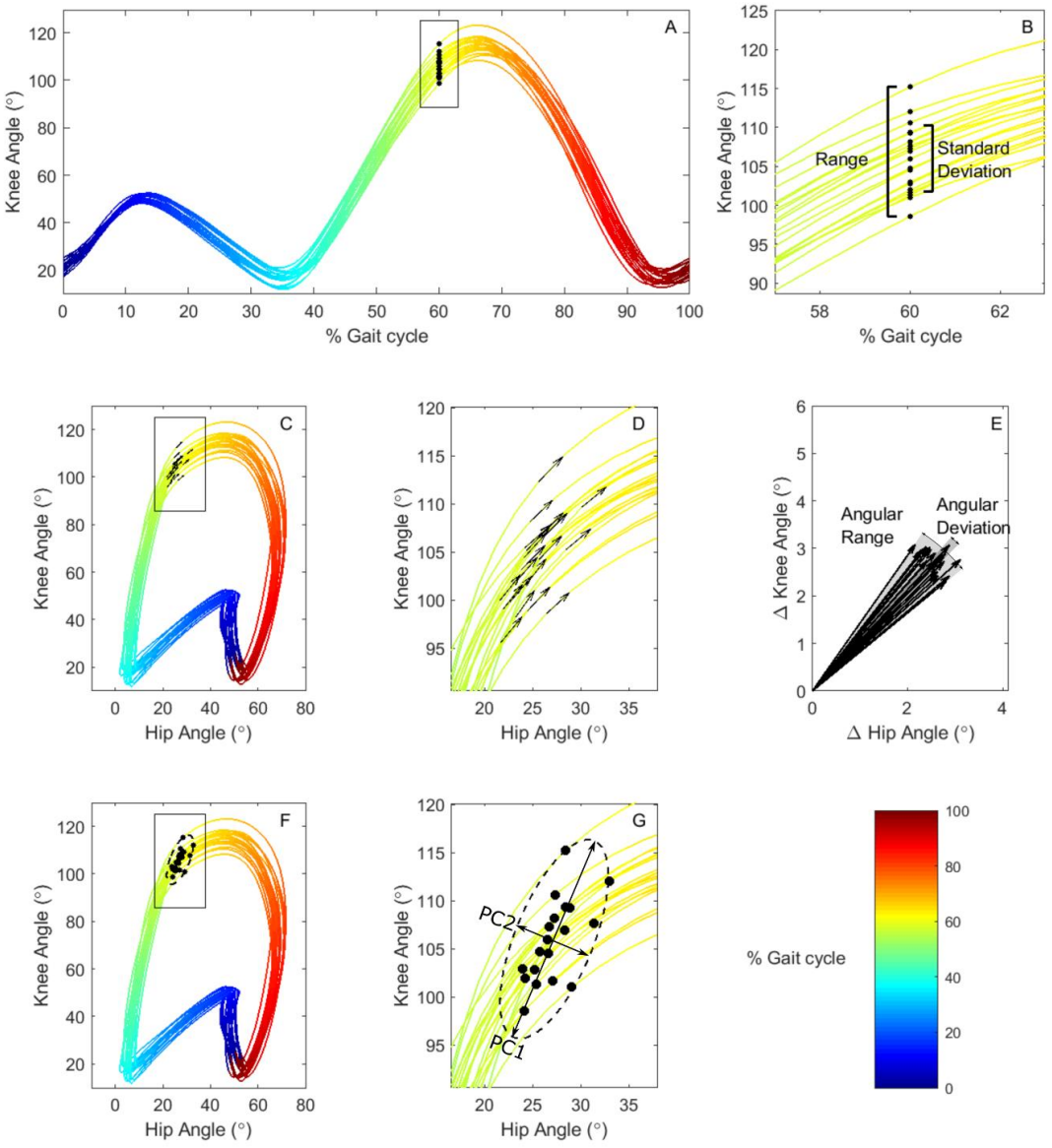


Figure 2.1. Comparison of exemplar univariate, circular and multivariate methods for calculating variability. A) Sagittal knee joint angle for 20 time normalised gait cycles (grey) from a single participant with the data points at a single time point (60% of gait) highlighted in black. B) A magnification of the area highlighted in A, demonstrating two measures of univariate variability: the range and standard deviation. C) Angle – angle plot of sagittal hip angle against sagittal knee angle for the same twenty gait cycles of time normalised data as in A (grey). Vectors joining the data points at 59 and 60 % of gait are highlighted in black. D) Magnified version of the area highlighted in C. E) Each vector from D normalised so that they originate from the same point (0,0). The angular range and angular deviation (calculated using circular statistics) are highlighted. F) The same gait cycle data as C but single data points from 60% of the gait cycle are highlighted, and an ellipse created about those points. G) Magnification of F demonstrating the two principal component (PC) axes (PC1 and PC2) of the PC ellipse that measure the greatest variability in the data at that time point (PC1) and the variation in the axis orthogonal to the axis of greatest variation (PC2). Here principal component analysis is demonstrated for two variables, but the same method can be applied to data sets of n variables to calculate n principal components.

statistics are vector coding and continuous relative phase (e.g. Hamill, McDermott and Haddad, 2000; Tepavac and Field-Fote, 2001; Heiderscheit, Hamill and van Emmerik, 2002). Multivariate measures quantify the magnitude or direction of spread of two or more movement variables and are therefore also considered to measure coordination variability (E.g. Figure 2.1F to G). Examples of multivariate measures of coordination variability include principal component analysis methods (e.g. Daffertshofer et al., 2004) and CI2 Area (e.g. Mulloy et al., 2019).

All measures of coordination variability that have been performed on time series data can then be represented as a time series for the duration of the movement, or can be averaged across phases of, or the entire movement to give a single average value of variability over specific time periods.

Structure of variability

In line with theories that suggest variability is not solely the result of random noise, several techniques have also emerged for measuring structure within variability. These techniques can be grouped into those that measure local stability or those that measure complexity. Local stability measures aim to quantify how movement responds to naturally occurring fluctuations by measuring how repeated trajectories converge or diverge from each other (e.g. Dingwell and Marin, 2006) or the from the mean (e.g. Granata and Lockhart, 2007). High local stability is thought to be important for the maintenance of global stability and is therefore often measured in relation to events that result in injury via a loss in stability.

Complexity (in the physiological sense) is the interaction of processes at different timescales to form non-random, structured behaviour (van Emmerik et al., 2016). Measures of complexity commonly found within the biomechanics literature have measured regularity at single spatio-temporal timescales by searching for recurring patterns within the data (e.g. Preatoni et al., 2010; Rhea et al., 2014) and fractality by measuring correlations in the data that occur at different time scales (e.g. Hausdorff et al., 1995). Complexity measures reflect the number of degrees of freedom and their interactions that allow a system to complete its function in a variety of ways. Thus, a decrease in complexity is thought to limit the ability to successfully adapt to perturbation.

These different aspects of variability (i.e. stability, complexity and magnitude) each offer their own contributions to improving our understanding of how movement behaviours emerge and the potential implications of those movement behaviours. Stability, complexity and magnitude are all separate concepts but various relationships have been proposed to explain how they interact with one another to create healthier or less healthy movement (van Emmerik et al.,

2016). For example, increased variability has been observed in the transition between two stable movement patterns and has therefore been proposed as a key factor in adaptability to switch from one stable movement pattern to another. This ability to adapt and change movement pattern is considered a healthy feature of movement. In another example it has been proposed that a reduction in complexity can manifest itself as a reduction in variability because there are fewer movement solutions available due to a reduction in the degrees of freedom. Once these reductions exceed a critical threshold, it is proposed that injury or disease may appear. Both examples and others like them are context specific and cannot be universally applied to associate complexity, stability and variability in all circumstances. The focus of this thesis lies in the vector coding measure of coordination variability magnitude and its application to lower limb musculoskeletal injury in sport therefore the interested reader is referred to other reviews on non-linear measures for more information on the topic (e.g. van Emmerik et al., 2016).

2.1.2 Applications of Variability

Variability and expert performance

In many sporting contexts, the ability to achieve a specific outcome consistently is a sign of expert performance and skill. The coordinated movements that lead to the consistent achievement of challenging motor tasks are however not always as consistent as the outcome. There is evidence within the literature to support that performers with high expertise can demonstrate more variable coordination than those who are less expert (Arutyunyan, Gurfinkel and Mirskii, 1969; Wilson et al., 2008). However, individuals with the same or lower skill levels have also demonstrated higher movement or coordination variability (Wilson et al., 2008; Wagner et al., 2012; Ko, Han and Newell, 2017). Variability therefore appears to be important for performance level, but it is not the only factor to consider and it is possible that relationships between coordination variability and performance level are measure, task and population specific. One context in which the dependency on measure can be demonstrated is when an error at the start of the kinetic chain is corrected at the end of the movement. In this instance if a random error was made early in a movement, it might propagate as the movement pattern progressed, providing an example of where coordination variability in one measure was negative for performance. If a joint later in the same kinetic chain adapted to correct for the previous error, and as a result the movement as a whole was successful, this would be an example of where variability in a different measure of the same movement had a positive impact on performance (e.g. Dounskaia, Van Gemmert and Stelmach, 2000).

Another factor to consider is that the success of replicating movements also relies on the consistency of the environment, but athletes often perform in varying conditions. Some athletes face/interact with varying opponents/teammates with different skills and tactics. In outdoor sports particularly, the environment may also be variable: The best coordination solution in one environment may therefore not be optimal in another. Thus, some athletes must be able to be variable when required, and it is not well understood if they are then also variable in invariant conditions where high execution variability is not a necessity.

Variability and learning

Given the associations between expert performance and variability it is also interesting to consider the role that variability plays in the learning of a skill, how variability changes as skilled performance develops and whether variability can be manipulated to accelerate learning. A large body of work has been conducted in the area of movement variability and skill acquisition, of which a full review is beyond the scope of this thesis. Important themes within that respect include but are not limited to: the freezing and freeing of degrees of freedom in learning a novel task (Vereijken et al., 1992), exploration and exploitation of variability to acquire and improve a skill (Müller and Sternad, 2004; Dhawale, Smith and Ölveczky, 2017) and the manipulation of constraints to influence variability and learning (Vereijken et al., 1992)

Variability, health and disease

In addition to the motor control of movement, variability has also been discussed in relation to human health. Goldberger, Peng and Lipsitz (2002) summarised the association between the structure of variability, health and disease by describing how the human body is constantly adapting to maintain homeostasis. The behaviours of the body that underpin homeostasis are complex in that there are many components to control which all interact separately with one another. Thus, Lipsitz and Goldberger proposed that regular, predictable behaviour was an indication of a loss of complexity and a potential sign of aging or disease. Vaillancourt and Newell (2002) expanded on the theory to suggest that increases in physiological complexity can also be seen with aging and or disease. Combining these hypotheses, Stergiou, Harbourne and Cavanaugh (2006) applied pre-existing theories of an inverted U relationship between complexity and predictability to health and disease or pathology via the system's ability to adapt (Figure 2.2).

Goldberger, Peng and Lipsitz (2002) and Vaillancourt and Newell (2002) presented their hypotheses as associating complexity with disease and health status as opposed to the magnitude of variability and made a clear differentiation between the two concepts that has

been reiterated in numerous works since then (e.g. van Emmerik et al., 2016; Ducharme and van Emmerik, 2018). Whilst it is important to differentiate between complexity (or other non-linear measures) and the magnitude of variability, some authors do suggest there can be relationships between them in some circumstances (i.e. a loss in complexity can manifest itself as a loss in variability with time, Hamill, Palmer and van Emmerik (2012)). Examples where measures of variability magnitude have differentiated between populations are possible evidence of where this association does exist. One article measured continuous relative phase variability of pelvic-thoracic coordination in healthy and recently diagnosed Parkinson's patients during treadmill locomotion (van Emmerik et al., 1999). The variability measured was lower in the Parkinson's group than the healthy group, but no differences were observed in traditional stride parameters. This suggested that coordination variability might be a more sensitive measure than others commonly used in a clinical setting.

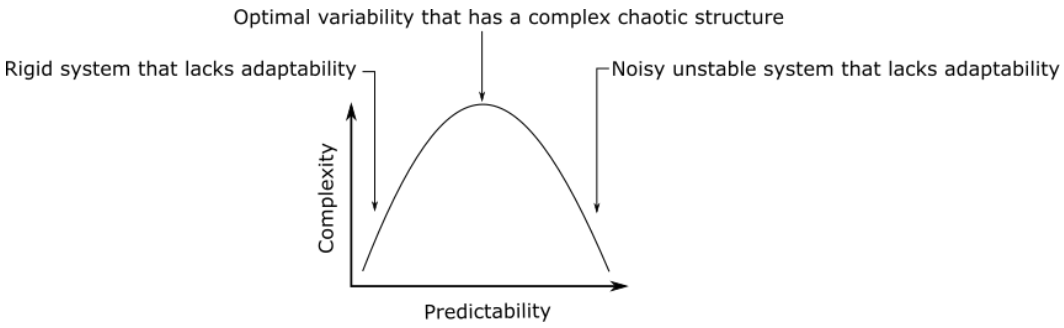


Figure 2.2. Relationship between predictability and complexity proposed in Stergiou, Harbourne and Cavanaugh (2006).

Furthermore, other measures of variability have also detected differences between clinical populations at more advanced stages of disease: a meta-analysis conducted by König et al. (2016) found the coefficient of variation of stride time was 80% effective in discriminating between participants with neurological pathologies (including peripheral, global, cognitive, cerebellar, brain injury and basal ganglia groupings) and compared to asymptomatic individuals with increases of 2.6% observed in the pathological groups. Ravi et al. (2020) also found greater variability in a number of spatiotemporal gait parameters such as stride time and stride length, but lower variability in step width for populations with neurological pathologies compared to healthy controls. The authors concluded that different pathologies present their own typical signature which has developed as a result of compensations for the effects of the

disorder and allows individuals to maintain function, i.e. sometimes variability can be low or high compared to a healthy population depending on the disorder and the task.

Variability and injury

The complexity – predictability model (Figure 2.2) has also been used to interpret the structure of variability in participants with injuries. A recent review summarised that the majority of studies of variability structure and lower-body injury or dysfunction in gait had detected more rigid control in injured populations compared to healthy controls (Strongman and Morrison (2020) reviewed 15 studies that calculated the Lyapunov exponent, entropy measures and fractal scaling). The authors suggested the more rigid control observed might render injured populations less able to adjust to changes and may be a relevant factor in the increased incidence of osteoarthritis following injury. An earlier review of ACL injuries and movement variability structure that summarised a series of publications from the same research group had additionally suggested that the decreased control their laboratory had observed in an ACL reconstructed population would lead to the same effect (increased risk of injury and osteoarthritis (Stergiou and Decker, 2011).

In addition to the findings from non-linear measures, associations between the magnitude of variability and injury had been made years before. In 1996 an abstract was published which concluded that persistently healthy participants had presented with greater variability in some kinetic parameters during a landing task compared to self-identified overuse injury-prone counterparts and that there may therefore be a relationship between musculoskeletal health or injury and variability (James, Dufek and Bates, 1996). A later landmark study observed a similar pattern in kinematic coordination variability measures at the start of the gait cycle between a healthy population compared to participant group with patellofemoral pain (Hamill et al., 1999). The authors suggested that the patellofemoral pain group may have more limited range of coordination patterns available compared to the healthy group that they could use without feeling pain and therefore that by running with lower variability, they minimised pain. In the same paper, Hamill et al. (1999) also proposed a mechanism by which the low variability they had observed could exacerbate the patellofemoral condition; the authors suggested low variability could lead to the repeated loading of tissues and may therefore contribute to an accumulation of microtrauma that would compound the problem.

As well as its application to overuse injuries, a connection has also been hypothesised between low variability and acute injuries. Mechanical testing has shown that repetitive loading can lead to degradation of the ACL (Wojtys, Beaulieu and Ashton-Miller, 2016) and one article has proposed that low variability in a population who had had ACL reconstruction compared to a healthy control group may have resulted in an accumulation of microdamage that

weakened the ACL and therefore lowered the threshold at which serious injury (i.e. tears and ruptures) occurs (Samaan et al., 2015a). It has also been suggested that 'excessively' high variability might be related to musculoskeletal injury (Hamill, Palmer and van Emmerik, 2012) but no mechanism was proposed by which this might directly occur.

There is a growing body of evidence that has sought to test the hypothesis that low coordination variability could be a contributing factor to injury, primarily focussed on lower limb injuries. A review from 2017 summarised published research into the relationship between the magnitude of variability and lower limb musculoskeletal injury (Baida et al., 2018). The review concluded that movement variability in groups with musculoskeletal injury was different to that of healthy individuals. They found an overall trend of greater variability in injured populations but suggested the direction of difference was not consistent across different injury types. For example, research investigating chronic ankle injury, anterior cruciate ligament reconstruction and patellofemoral pain syndrome had detected more examples of greater variability in the injured populations than of less variability or no difference in variability, but the one research study investigating patellar tendinopathy observed lower variability in the injured group. The general trend for increased variability in the injured populations was the opposite finding to that which the authors hypothesised and there has been no mechanism proposed as to why the magnitude of variability might directly be linked to injury. Numerous authors have warned against assumptions that the magnitude of variability can be used to infer complexity (Goldberger, Peng and Lipsitz, 2002; van Emmerik et al., 2016) but some authors have also explained that changes in complexity can lead to changes in the magnitude of variability (Hamill, Palmer and van Emmerik, 2012). This could provide a possible explanation for why increased variability has been observed in injured populations, but it must be considered that it relies on the assumption that variability and complexity are correlated. Furthermore, whilst the review is helpful in summarising the research to date, the overall trend of greater variability in injured populations was based on results from studies that used a number of different measures of variability, in different movements and of populations with different injuries. Research has found that different measures of variability do not always agree (Miller et al., 2010), and that different injuries may elicit different responses (Baida et al., 2018). This poses a general challenge for the research area as it is hard to understand whether contrasting results are caused by different methodologies and subject groups or because the results are not generalisable to wider populations than the research study sample.

A key consideration in this field of research is that the evidence available is largely cross-sectional. Several authors (e.g. Hamill, Palmer and van Emmerik, 2012; Baida et al., 2018) have highlighted the need for prospective research to understand if these different levels of

movement variability are present prior to injury (and therefore a possible causative factor) or purely occur as a result of injury. A recent prospective publication measured baseline coordination variability in running, asked participants to self-report pain for a 6 month period and then compared all the baseline data from those who had reported pain during this period to those that had not (Desai and Gruber, 2020). The authors reported that coordination variability was higher in the group that went on to report injuries. More specifically in one example, the higher variability was observed in in-phase knee – shank motion during initial stance, a coordination pattern that the authors had identified as mechanically unsound. The greater coordination variability observed was suggested as a contributing factor to the injuries reported. This prospective evidence is a useful contribution to the area of research, but the authors still highlight a need for a larger scale prospective trial and longitudinal research that measures coordination variability before during and after injuries are sustained. A more thorough understanding of the repeatability of coordination variability measures will add context to such investigations by supporting whether any statistical differences or changes are of a meaningful magnitude. There is a dearth of research providing information about the repeatability of coordination variability measures in movements commonly used to investigate the coordination variability – injury hypothesis for the lower limbs such as running and cutting. The focus of this thesis is therefore to specifically investigate the repeatability of vector coding measures of coordination variability

2.2 Coordination and Coordination Variability Measures

Human movement is generated by controlling the multiple interacting components of the body. One positive aspect of these interactions is the potential to correct errors that occurred earlier in the kinetic chain, but some interactions also have the potential to be harmful. For example, concurrent hip extension and knee flexion has under certain conditions been demonstrated to result in anterior movement of the tibia that increases ACL strain and therefore also risk of ACL injury (Hashemi et al., 2011). Understanding how components interact can therefore be an important step to analysing movement.

The two measures which have predominantly been used to measure coordination and its variability in relation to lower limb injuries are vector coding and continuous relative phase (CRP). Vector coding and continuous relative phase measures both quantify the interactions between two variables, which are typically joint or segment angles, selected according to their relationship with a specific injury. The methods are similar in that they each calculate a time series for the duration of the movement that represents coordination. When multiple repetitions of a movement are measured, multiple coordination time series are computed and the variation of these can be calculated at each percentage of the movement cycle to generate

a time series that indicates how the variability of coordination changes throughout the movement. Researchers can then analyse the coordination variability time series or can average coordination variability over different movement phases to produce discrete measures of coordination variability. In contrasting the two methods vector coding has been described as an easier tool to use in clinical applications but has been criticised for losing the higher order, spatio-temporal information (i.e. measures include those of angular distance and of time) contained within continuous relative phase that may facilitate the detection of subtle changes in movement patterns (van Emmerik, Miller and Hamill, 2014). However, CRP can only be applied to data that follows a largely sinusoidal pattern (Peters et al., 2003). Many of the segment and joint movements relevant for lower limb injury are not sinusoidal in nature. Vector coding was therefore selected as the focus of this thesis.

2.3 Vector Coding

Vector coding has been applied in several different research applications to measure the coordination between paired joint or segment angles (e.g. Eslami et al., 2007; A. Brown et al., 2016; Beitter, Kwon and Tulchin-Francis, 2020) and a number of methods have also been developed that quantify the variability of these interactions. Vector coding techniques measure the magnitude of variability (as opposed to the structure, as with non-linear measures) and within vector coding measures there are currently examples of both circular and multivariate methods for calculating coordination variability.

2.3.1 Origins

The angle – angle plot (also known as a relative motion plot or cyclogram, Figure 2.3) was first presented by Grieve (1968) as an economical way of assessing the relationship between the movement of two body segments (collectively referred to as a coupling). Initially, the angle – angle plot was interpreted qualitatively but since then various methods for quantifying and comparing the patterns observed on the angle – angle plot have been proposed as measures of coordination. Measures of the variability of those interactions were then also developed (coordination variability measures).

In the 1970s and 80s, a number of authors explored the use of angle – angle plots for investigating the origins of movement control and for clinical uses (e.g. Cavanagh and Grieve, 1973; Milner, 1973; Soechting and Lacquaniti, 1981). One solution to quantifying the angle – angle plot measurement Whiting and Zernicke (1982) calculated the similarity between two angle – angle plots using a chain encoding method (Freeman, 1961): the angle – angle plot was fitted to a unit grid and portions of the relative motion plot were transformed into digital elements that approximated the direction of vectors on the relative motion plot to the closest

multiple of 45 degrees (Figure 2.4). Cross correlation was then used to derive a 'recognition coefficient'. A recognition coefficient of one represented the same shaped pattern and orientation had been observed on both graphs but did not provide any indication of variation in the magnitude of the shape of the two angle – angle plots.

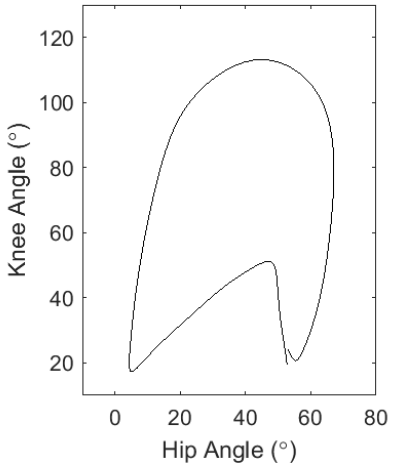


Figure 2.3. Example angle – angle plot of sagittal hip and knee joint coupling for a single gait cycle.

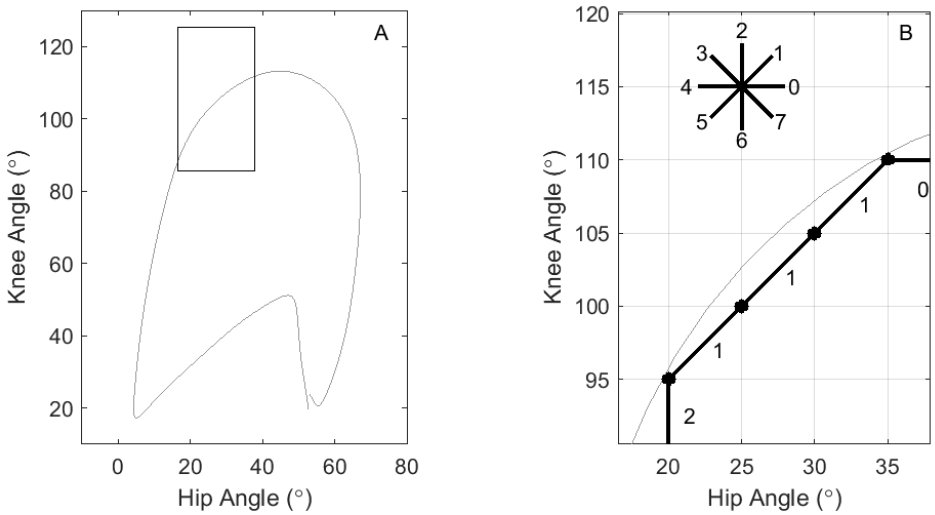


Figure 2.4. Whiting and Zernicke (1982) chain encoding method. A) Example angle – angle plot for sagittal hip – knee joint coupling of one gait cycle. B) Magnified portion of A demonstrating the chain encoding method used by Whiting and Zernicke (1982) where the data series pattern was matched to a grid and the direction of the matched pattern was coded between 0 and 7.

Sparrow et al. (1987) suggested an advance on this approach for use in human movement research by measuring the angle that each vector (formed between consecutive data points on

the angle-angle plot) made with the horizontal (Figure 2.5). They proposed that the previous chain encoding method unnecessarily fitted the curve to the unit grid given that the coordinates of the relative motion plot were known, and computing inefficiencies were no longer a limitation. The method used a revised cross-correlation formula to compare the similarity of angle-angle plots. This calculation was affected by shape, magnitude and orientation but was still limited to comparing only two angle – angle plot traces at any time.

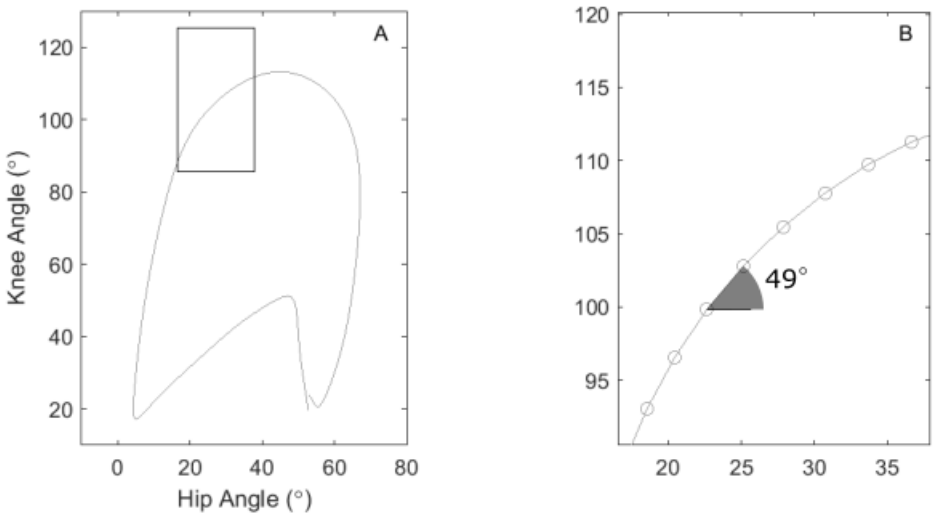


Figure 2.5. Sparrow et al. (1987) vector coding method. A) Example angle – angle plot for sagittal hip – knee joint coupling of one gait cycle. B) Magnified portion of A demonstrating the formation of vectors between consecutive data points as first suggested in Sparrow et al. (1987). The measure of similarity calculated the angle that each of these vectors made with the horizontal was then calculated as is demonstrated for the vector joining data points at 59 and 60% of the gait cycle.

Sidaway, Heise and Schoenfelder (1995) then highlighted that many researchers were using angle – angle plots, but either provided purely qualitative interpretations, or used correlation statistics which were only suited to linear relationships between the two angular components, the results of which were relative to the variability of the measures used to calculate it. Sidaway, Heise and Schoenfelder (1995) proposed a new technique, the Normalised Root Mean Square (NoRMS), that calculated the resultant distance (R) between each cycle and the mean cycle and normalised this according to the resultant excursion of the mean angle-angle curve over the course of the cycle to give a percentage value of variability. This technique allowed multiple angle – angle plots to be compared but did not use information from the vectors between points, therefore would not be classified as a traditional 'vector coding' technique.

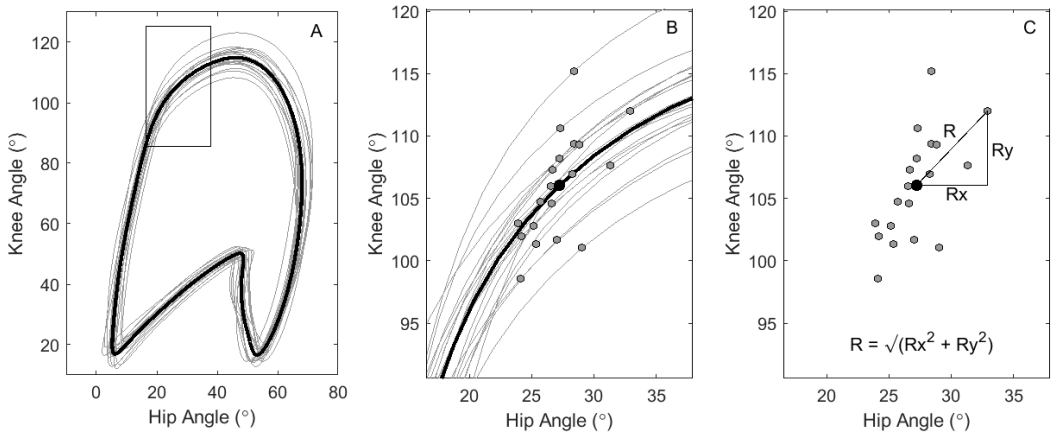


Figure 2.6. Sidaway, Heise and Schoenfelder (1995) Normalised Root Mean Square (NoRMS) variability method. A) Example angle – angle plot for sagittal hip – knee joint coupling of twenty gait cycles (grey) and their average (black). B) Magnification of A with data points at 60% of each respective gait cycle highlighted with grey dots and the mean of these represented by the black dot. C) Visualisation of the calculation of R (distance of each data point from the mean). Sidaway, Heise and Schoenfelder (1995) calculated the average root mean square of R for each cycle and normalised the result according to the resultant excursion angle – angle curve as a measure of variability of the angle – angle plot.

Hamill, McDermott and Haddad (2000) proposed a method based on the vector coding approach of Sparrow et al. (1987) which calculated the angle between consecutive data points for each repetition as a measure of coordination (Figure 2.7C). Hamill, McDermott and Haddad (2000) also suggested that circular statistics could be applied to represent the variation in the direction of multiple vectors. Because this method measured the variation in the vectors (i.e. the ratio of change in one variable compared to another as demonstrated in Figure 2.7D) it was fundamentally different to the NoRMS method that quantified the variation in the position of each cycle on the angle – angle plot. Whilst the use of circular statistics allowed multiple angle – angle cycles to be compared simultaneously this method did not account for variations in the vector length. This technique was applied in a research study for the first time in a paper published in 2002 (Heiderscheit, Hamill and van Emmerik, 2002) with a small modification . The method proposed by Hamill, McDermott and Haddad (2000) had calculated a measure of angular variation on a scale of 0 to 1 (angular dispersion), whereas in the Heiderscheit, Hamill and van Emmerik (2002) paper, this measure was converted to be measured in degrees (angular deviation).

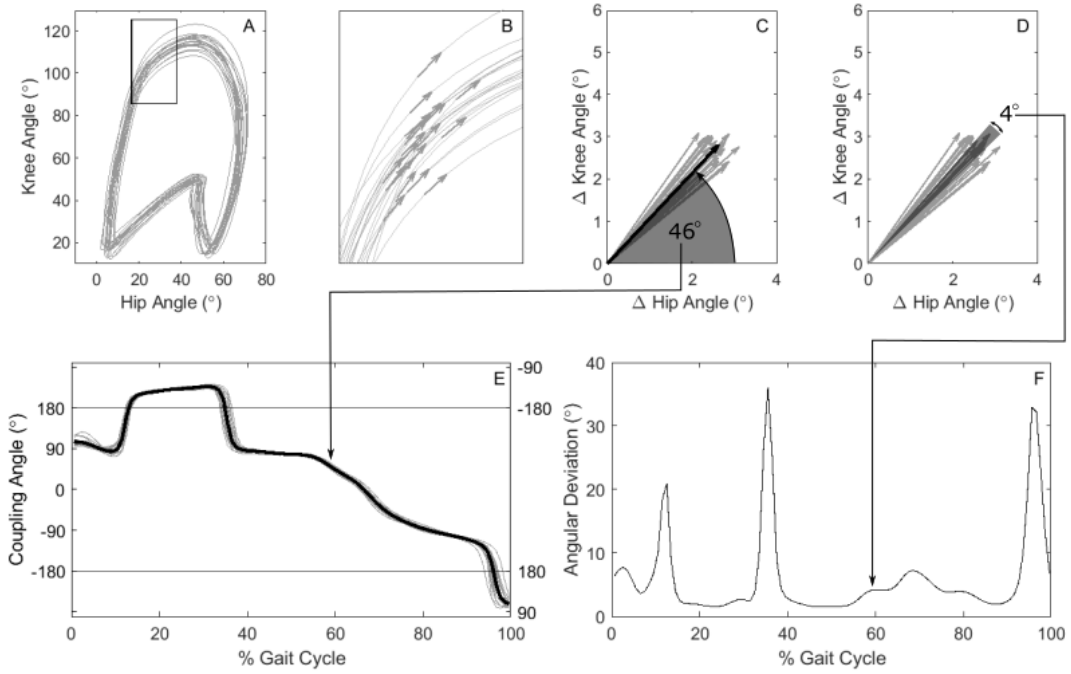


Figure 2.7.Heiderscheit, Hamill and van Emmerik (2002) vector coding coordination variability method. A) Example angle – angle plot for sagittal hip – knee joint coupling of 20 gait cycles B) Demonstration of the vectors between data points at 59 to 60% of each gait cycle. C) Visualisation of all 20 vectors shown in B normalised to the same starting point (grey) and the mean vector (black). The angle the mean vector makes with the horizontal is used as a measure of coordination in the method first proposed by Hamill, McDermott and Haddad (2000). D) Visualisation of all 20 vectors shown in B normalised to the same starting point (grey) and angular deviation of the 20 vectors is labelled. This value was used as a measure of coordination variability by Heiderscheit, Hamill and van Emmerik (2002) and in many publications since then E) Example of coupling angle as a time series across the gait cycle. F) Example of angular deviation (a measure of coordination variability) as a time series across the gait cycle.

Tepavac and Field-Fote (2001) presented another variation on the Sparrow vector coding method. Their measure included the same angular dispersion value that had been suggested by Hamill, McDermott and Haddad (2000), but had an additional component that accounted for variation in the length of the vector (Figure 2.8 D&F). The directional and length components were combined to provide a single measure of coordination variability (Figure 2.8G).

During the development of this thesis (2015-2020) further methods have also been proposed that quantify the data contained within angle – angle plots. In 2017 the CI2 method was proposed for calculating and comparing confidence intervals of two bivariate time-series (Mullineaux, 2017). This method formed an area about the mean bivariate time series via a sequence of steps: ellipses were created for each time normalised data point (Figure 2.9B), vertices were then placed at the point where a vector perpendicular to the direction of the mean

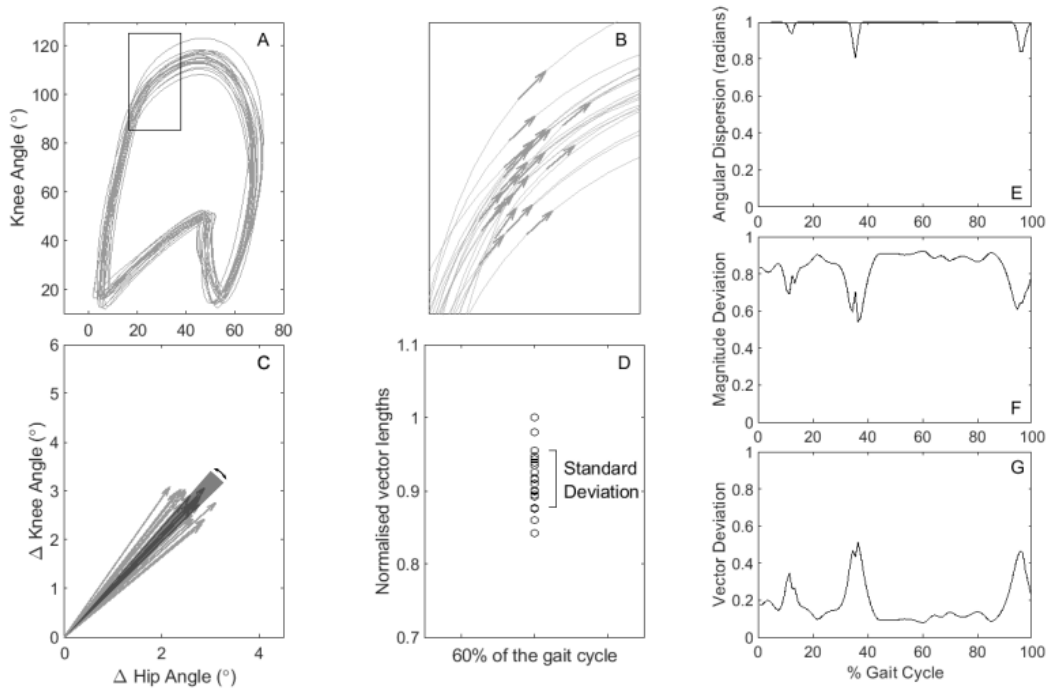


Figure 2.8. Tepavac and Field-Fote (2001) vector coding coordination variability method. A) Example angle – angle plot for sagittal hip – knee joint coupling of 20 gait cycles B) Demonstration of the vectors between data points at 59 to 60% of each gait cycle. C) Visualisation of all 20 vectors shown in B normalised to the same starting point (grey) and demonstration of angular dispersion of the 20 vectors. D) Each dot represents the lengths of all the vectors in C normalised by the value of the longest vector from the twenty cycles between 59 and 60% of gait. The standard deviation of the normalised vector lengths is then calculated and normalised according to the maximum standard deviation possible for n values bounded between 0 and 1 This is subtracted from 1 to give the values which are observed in F. E) Example of angular dispersion as a time series across the gait cycle. N.B. values close to one represent no angular dispersion and values close to 0 represent the maximum dispersion possible. F) Example of vector magnitude deviation as a time series across the gait cycle. G) The Tepavac and Field-Fote (2001) vector deviation metric (magnitude deviation multiplied by angular dispersion) presented as 1 − vector deviation so that higher values represent greater variability Mullineaux and Uhl (2010))

bivariate time series intersected the ellipse boundary at each time point, and convex quadrilaterals were created from these vertices (Figure 2.9C). This method identified the 95% confidence intervals about a set of bivariate data (Figure 2.9D). It could then be used to determine when two sets of bivariate data (the example provided was of two angle variables) were different to one another (i.e. the convex quadrilaterals formed from each set from the same time point in the movement did not overlap) or were similar (convex quadrilaterals did overlap). The area of the convex quadrilaterals could be used a measure of variation in the angle – angle plot (Figure 2.9E). The example presented did not use information from the vectors between points, therefore would not be classified as a traditional 'vector coding' technique.

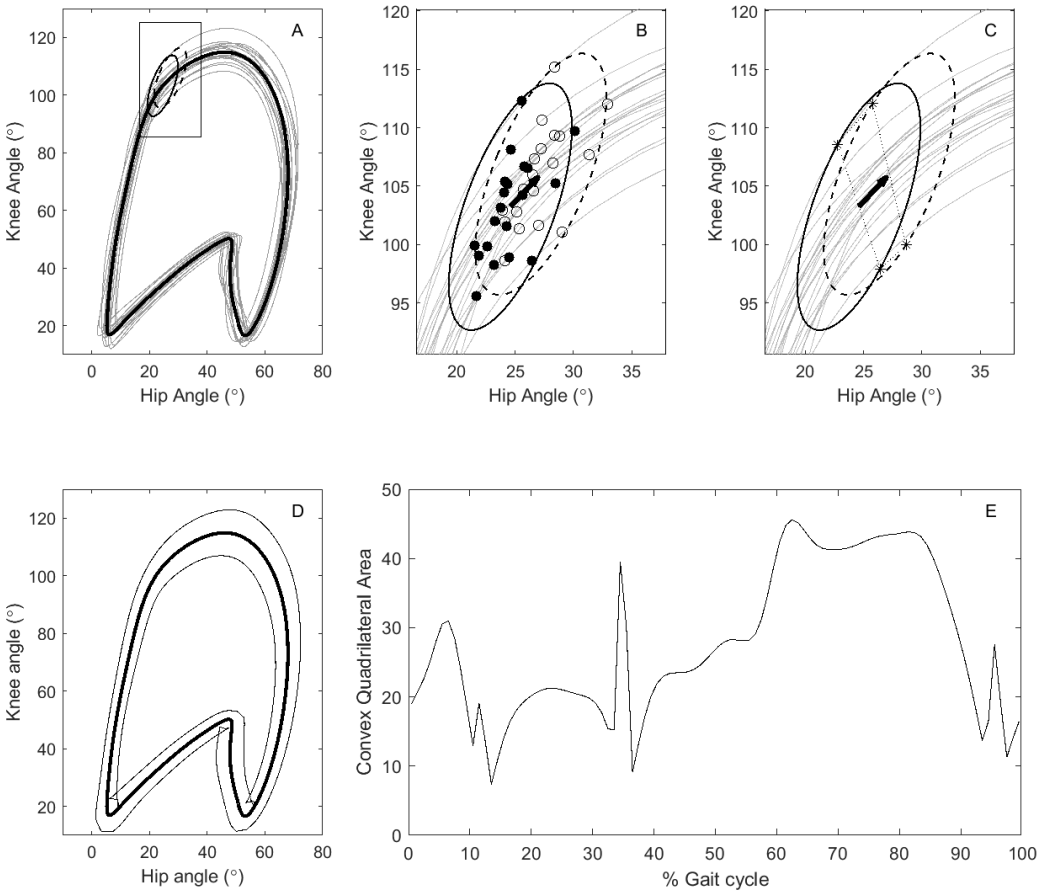


Figure 2.9. Mullineaux (2017) CI2 method for comparing confidence intervals of bivariate plots. A) Example angle – angle plot for sagittal hip – knee joint coupling of twenty gait cycles (grey) and their average (black). B) Magnification of A with data points at 59 and 60% of each respective gait cycle highlighted with filled circles and unfilled circles respectively. Ellipses were created about each set of points (59% solid, 60% dashed). C) Convex quadrilaterals were created by finding and joining the points (*) where lines perpendicular to the mean vector (dotted lines) intersected their respective ellipse. D) The 95% Confidence Intervals (thin line) about the mean (thick) angle – angle trace. E) The area of the convex quadrilaterals at each point in the time series can be plotted as a bivariate measure of variability of the bivariate plot as suggested by Mulloy et al. (2019).

In 2019 an extension to the CI2 method was proposed that provided a measure of variability in the bivariate time series data by summing the areas of each convex quadrilateral (Mulloy et al., 2019). In the specific example presented, the two variables that formed the bivariate plot were both joint angular velocities. The first vector coding methods calculated the changes in consecutive joint angle data points to create vectors used for further calculations. When the temporal distance between each data point is equal, there is often a strong correlation between the difference in joint angle ($\Delta\theta$) and the joint angular velocity ($\Delta\theta/t \approx \delta\theta/\delta t \approx \omega$) therefore the coordination variability calculated in this example was comparable in concept to other vector coding methods.

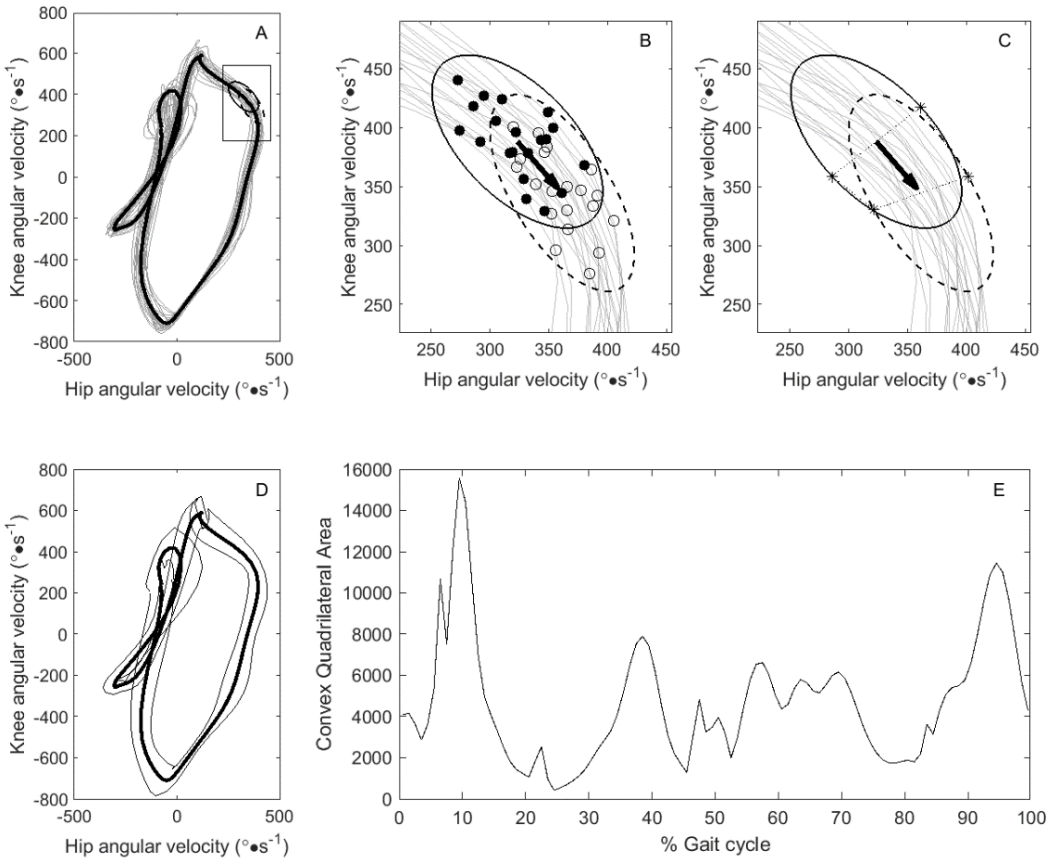


Figure 2.10. Mulloy et al. (2019) CI2Area method with angular velocity inputs for measuring coordination variability. A) Example angular velocity – angular velocity plot for sagittal hip – knee joint coupling of twenty gait cycles (grey) and their average (black). B) Magnification of A with data points at 59 and 60% of each respective gait cycle highlighted with filled circles and unfilled circles respectively. Ellipses were created about each set of points (59% solid, 60% dashed). C) Convex quadrilaterals were created by finding and joining the points (*) where lines perpendicular to the mean vector (dotted lines) intersected the respective ellipse. D) The 95% Confidence Intervals (thin line) about the mean (thick) angle – angle trace. E) The area of the convex quadrilaterals at each point in the time series can be plotted as a bivariate measure of variability of the angular velocity – angular velocity plot.

2.4 Validity, Accuracy, and Reliability of Vector Coding Coordination Variability

"It is generally agreed that the usefulness of measurement results, and thus much of the information that we provide as an institution, is to a large extent determined by the quality of the statements of uncertainty that accompany them." (Taylor and Kuyatt, 1994).

When taking any kind of measurement it is imperative to understand the validity, accuracy and reliability of that measure: validity refers to the degree to which a measurement measures what it claims to measure, accuracy refers to how closely a measurement reflects the true value and reliability refers to the similarity between repeated measures of the same quantity.

Together, they allow the user to make informed decisions about which methods are most appropriate to use in a given scenario, what sample size is required to give future studies sufficient power (Hopkins, 2000) and how to interpret data with regards to: what inferences can be drawn from the data, and what magnitude of change indicates a methodologically meaningful change. There has been little comment on these aspects in relation to measures of movement coordination and coordination variability in relation to musculoskeletal lower limb injury. Each has been addressed in turn below, summarising what information is available in the literature and highlighting opportunities for future learning and improvement specifically in relation to the application of vector coding. In many cases the same considerations are also relevant for other measures of coordination variability and applications outside of injury.

2.4.1 Validity

There are several subcategories of validity (e.g. construct, criterion, concurrent, ecological, face, internal and external) and the validity of a test can be assessed taking each of these sub categories into account. Many of the validity subcategories are affected by factors such as the population measured and the data collection protocol (e.g. external validity) which must take an entire study design into consideration. Here, I aim to specifically discuss the validity of coordination variability analysis with regards to its concurrent, construct and internal validity.

Concurrent validity traditionally tests whether an un-validated measure correlates well with one that has been validated. Coordination variability is a concept that has been proposed to represent movement coordination dynamics, but multiple methods have been put forward as to how this can be achieved. None of these measures have been officially validated, nor would it be an easy task to do so, therefore the different measures must simply be compared with one another without a gold standard. The different methods measure different properties of movement coordination and therefore their outputs are not necessarily directly related to one another. Vector coding and continuous relative phase (Miller et al., 2010) and root mean square difference methods (Mullineaux and Wheat, 2018) have been compared with one another by applying each method to the same dataset. Vector coding, continuous relative phase and root mean square difference measures were found not to convey the same information about variability as different signal patterns across a gait cycle were observed for each measure. This is potentially confusing for users given that all methods are described as tools for measuring coordination variability and brings into question what kind of variability is important to measure. The second relationship between the magnitude of coordination variability and injury presented in 2.1.2 (page 34) was based on the assumption that the magnitude of variability measured might reflect the complexity of the system controlling that movement (Hamill, Palmer and van Emmerik, 2012). Whilst this can provide a possible

explanation for an observed result, a more valid approach would be to measure the structure of variability directly. Thus, it is important to select a method according to how well it represents the hypothesis the research aims to test and to provide clear rationale for the choice.

Construct validity is commonly thought of as the extent to which a test measures that which it claims to measure. This thesis focuses on the application of vector coding coordination variability in relation to lower limb musculoskeletal injury. In the case of the coordination variability – injury model, the hypotheses are based on two premises. The first is that in conditions of low coordination variability, musculoskeletal tissue is repetitively loaded during repeated movement patterns such as gait to an extent where the biological structures are damaged more quickly than the body is able to repair them and the damage manifests as a chronic injury (Hamill, Palmer and van Emmerik, 2012). Alternatively, the same mechanism could lead to lower acute injury loading thresholds because structures have become weaker as a result of sustained microtrauma (e.g. Wojtys, Beaulieu and Ashton-Miller, 2016). All coordination variability measures derived from kinematics quantify how varied the interactions of coupled joint or segment movements are, but do not quantify the loads experienced by individual biological structures. Future research into specific injury types would benefit from understanding how variability in kinematic measurements is associated with the variation in load experienced in the injured tissue via cadaver or simulation studies to better support the construct validity of coordination variability measures and the repetitive loading hypothesis.

Furthermore, the rate at which biological tissues are damaged is dependent not only in the variation of loading but also the volume (Drew and Finch, 2016; Nielsen et al., 2018). The interaction between these has not been considered in variability-injury research but could be fundamental to the proposed mechanism and a confounding factor when measuring kinematic variability and injury occurrence. Future research should consider these factors to improve the internal validity of their research when investigating the associated between coordination variability and variability based on a repetitive loading theory.

2.4.2 Accuracy

Accuracy is defined as the “closeness of the agreement between the result of a measurement and the value of the measurand” (Taylor and Kuyatt, 1994). The accuracy of coordination variability measures can be considered in terms of the accuracy of the inputs to calculating coordination variability, and the robustness of the method to measure coordination variability in appropriate data sets. In considering a single measurement, accuracy may also be affected by the repeatability of the coordination variability measurement, which will be addressed in detail in a later section.

Accuracy of kinematic inputs

To date, the most common technique for capturing the joint and segment angle measurements used in vector coding has been marker-based motion capture. This method for measuring kinematics involves the calculation of anatomical coordinate frames for each segment of the body based on the positioning of anatomical markers in relation to a global coordinate system. At the same time, the positions of tracking markers in relation to each anatomical coordinate system are noted. The positions of at least three of these tracking markers per segment (Laribi and Zeghloul, 2020) are then measured during a movement or task. A coordinate system is constructed for the tracking markers of each segment and with the knowledge of how the positions of the tracking markers relate to each segment coordinate system. Segment positions are then calculated in relation to the global coordinate system. As with all measurements there is a degree of error associated with this process which can arise from aspects such as: 1) incorrect positioning of the anatomical markers (e.g. Jensen et al., 2016), 2) movement of the tracking and anatomical markers relative to the bony segments which they represent due to soft tissue artefact (STA) (Benoit, Damsgaard and Andersen, 2015) 3) errors in the measured positions of the anatomical and tracking markers (Gorton, Hebert and Gannotti, 2009) and 4) violations of biomechanical model assumptions such as that each segment is a rigid body.

Errors in the measured positions of the markers are expected to be very small (sub millimetre) as the accuracy of motion capture systems is high (Gorton, Hebert and Gannotti, 2009; Eichelberger et al., 2016). However, errors in the original anatomical coordinate system definitions and the movement of tracking markers in relation to the segment are difficult to avoid with marker-based technology. Small differences in the placement of anatomical markers can lead to changes in the orientation of the segment coordinate system (Jensen et al., 2016). The effects of this on joint angle measurements alone are unpredictable (Akbarshahi et al., 2010). This is partly because the change in the orientation of the segment coordinate system does not cause a consistent translation in the measured segment angle across the gait cycle, but varies as movement occurs because different magnitudes of cross-talk between the planes of motion are present depending on the positions of the segments (Akbarshahi et al., 2010). Consequently, the effect of anatomical marker placement on coordination variability that is calculated from the angle measurements is also not well understood.

In addition to this, current markersets often fix rigid clusters of markers to the segment by tape and strapping. In lower limb analyses, the movement of the markers is intended to represent the movement of the load bearing bone within the segment to which they are attached. The position of the cluster in relation to the position of the bone will vary as the soft tissue to which the rigid cluster is attached moves relative to the bone. The amount of error this soft tissue

movement causes depends on the movement performed and the participant. For example: impacts and muscle contractions can cause the surface of the skin (and therefore the orientation of the rigid cluster) to move relative to the bone and participants with greater body mass indexes (due to muscle or fat mass) may have more movement of the cluster compared to someone with a lower body mass index (Lin et al., 2016). The effects of this on variability specifically are unknown but a doctoral thesis on vector coding coordination variability (Wheat, 2005) suggested that errors in the estimation of bone pose due to STA are unlikely to exert large effects on variability measures, because such variation is largely systematic (Holden et al., 1997). However, the author suggested that further work is required into the effect of STA on coordination variability.

The different sources of error combine to form a total error associated with marker-based motion capture data. Several studies have looked to quantify the total error observed during different movements. This has been achieved by collecting marker-based motion capture data from markers attached to the skin at the same time as 'gold standard' motion capture methods such as dual fluoroscopy analysis (e.g. Fiorentino et al., 2017), bone-pin (e.g. Reinschmidt et al., 1997; Benoit et al., 2006) and phase-contrast magnetic resonance imaging (e.g. Sheehan, Zajac and Drace, 1997). These studies have found that joint angle measurements from stereophotogrammetry (marker-based motion capture) can introduce steady state errors and errors that change throughout the gait cycle. The magnitude of these differences varies according to the movement performed, the joint angle measured, and the participant involved. For example in walking, skin mounted marker measurements from one participant suggested an average difference across multiple trials of between 7 and 10º greater abduction at the knee over the course of the stance phase compared to bone pin measurements (Benoit et al., 2006). For another participant skin markers suggested 2º more adduction at the start of stance, but 10º greater abduction at the end of stance and for a third participant, skin markers provided estimates that remained within 4 degrees of the bone pin joint angle measurements throughout stance (Benoit et al., 2006). However, studies into the error in marker-based motion capture have not focussed on how well variability of angle measures derived from marker-based motion capture correlate with gold standard motion capture methods. The difference may be small, or indeed favourable compared to the difference observed in the absolute angle but is nonetheless unknown.

Accuracy of the vector coding method

In addition to the accuracy of the motion capture systems providing the data for vector coding, the method of measuring coordination variability itself must also be considered. In one of the first presentations of the method, Heiderscheit, Hamill and van Emmerik (2002) noted that

proximity of data points could affect the calculation of variability and that the coupling angle (and therefore coupling angle variability) would be sensitive to small displacements in the data when data points were close to one another on the angle – angle plot. If the observation about the proximity of data points made by Heiderscheit, Hamill and van Emmerik (2002) were correct, and there was evidence that the proximity of data points in real biomechanical data might elicit the aforementioned sensitivity in the data, the accuracy of coordination variability measures based on coupling angles could be questioned when the proximity between data points on the angle – angle plot was small. No other research paper to have used the methods first demonstrated by Heiderscheit, Hamill and van Emmerik (2002) or Tepavac and Field-Fote (2001) has further investigated the effects of data point proximity despite its potential significance.

Furthermore, the vectors within vector coding are defined by the differences ($\Delta\theta$) between consecutive data points on the angle – angle plot (i.e. the x and y components of the vector are defined as the change between data point points in the variable plotted on the x and y axis of the angle-angle plot respectively). Each vector therefore represents the average dynamics of change in each of the coupling angle components between two time points. Traditionally angular dynamics are represented by angular velocities which are not, in general, equal or proportional to $\Delta\theta$ (Winter, 2009). The possible implications of this for vector coding measures has not previously been considered.

2.4.3 Reliability

Measurement reliability is a concept related to how certain an individual can be that if they repeated the same experiment, their results and conclusions would be the same. In human measurements, no single value can be universally assigned to represent how reliable, reproducible or repeatable a measurement is because the value is affected by the time between testing and the sources of variance (such as biological, measurement and environmental, Equation 2.1) that might be present between those tests (Beckerman et al., 2001). Thus, it is important, where possible, for researchers to include investigations into the repeatability of the measures they use. As this is not always possible, research aimed at providing benchmark repeatability values can also be valuable.

There are two forms of reliability: *absolute reliability* concerns the confidence that a measured value will take the same value when measured again in the future, whereas *relative reliability* refers to the likelihood that any individual measurement will be similarly ranked compared to other measurements in a repeated test. In order to avoid having to specify the type of reliability in the rest of this thesis, absolute reliability will hereafter be referred to as repeatability.

Repeatability

Repeatability, also referred to as a measure of agreement or absolute reliability is defined as "closeness of the agreement between the results of successive measurements of the same measurand carried out under the same conditions of measurement" (Taylor and Kuyatt, 1994). It is an important concept to understand when interpreting data as it can help researchers understand whether the differences they observe are greater than those that can be expected due to random fluctuations in the measure that may appear as a result of measurement error or biological variation. The repeatability of a measure is one of multiple factors which affect the statistical power of a research study investigating changes over time but is also valuable when interpreting differences between groups.

Measurements of repeatability

Within sport science and health research, until recently most data, even if multi-dimensional in nature, has been reduced to discrete values. Literature on how to assess repeatability within the sport science field has therefore largely reflected this. Atkinson and Nevill (1998) summarised three methods for assessing repeatability (referred to in their work as absolute reliability): the standard error of measurement (SEM), coefficient of variability (CV) and Bland and Altman's 95% level of agreement (LOA).

The SEM represents the range above or below an observed score within which there is a 68% chance the hypothetical true score falls, for the average participant from the data set and is based on the assumption of normally distributed errors and homoscedasticity (Atkinson and Nevill, 1998).

The Bland Altman LOA is based upon a similar calculation of variance to the SEM but recommends an initial assessment of systematic bias and scedasticity and calculates a range within which there is a 95% chance the hypothetical true value falls. Homoscedasticity is a feature of data whereby the magnitude of variance is consistent across all values of the data (Figure 2.11A) but with heteroscedasticity variance can change according to the value of the data (Figure 2.11B). In heteroscedastic data, if the relationship between variance and the magnitude of the measure demonstrates that variance increases with increasing values, a log transform can be applied to the data (Bland and Altman, 1996b). The log transform differentially decreases larger values by a greater amount and so this method can create a dataset where variance is more constant across the range of values (e.g. Figure 2.11C). If the transformed data set is judged to be homoscedastic, statistical calculations can be applied to the transformed data to produce a ratio. The range within which 95% of hypothetical true

values should fall can then be calculated by multiplying or dividing the measure by the ratio to give upper and lower boundaries respectively (Bland and Altman, 1996b).

In addition to the popular LOA method, Bland and Altman (1996a) proposed a further stage of calculation to compute what they termed a 'repeatability coefficient'. By multiplying the 95% boundaries by √2 they proposed that a range of values is created (e.g. Figure 2.11D) and that any values measured which fall outside of this range are likely to represent a real change. This same method is now more frequently referred as the 'smallest real difference' (e.g. Beckerman et al., 2001) or 'minimum detectable change' (e.g. A. Bates, McGregor and Alexander, 2016; Barrios and Willson, 2017)

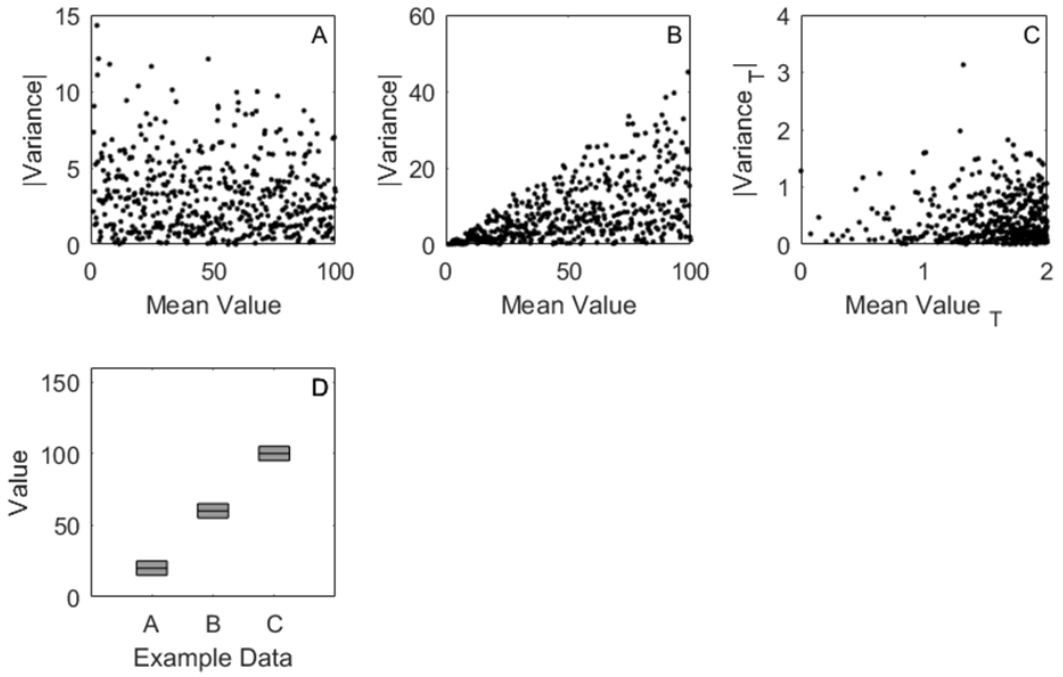


Figure 2.11. Examples of different relationships between the mean value of multiple sessions (x-axis) and the variance of data taken on the same participant across multiple sessions (y-axis). A) The range of variance observed appears to be consistent across the range of mean values, so the data is homoscedastic. B) The variance seems to be different across different mean values, so the data is heteroscedastic. In this particular example, variance is greater for greater mean values. C) The data in B were log transformed and the relationship between mean value and variance is less obvious D) Demonstration of minimum detectable change ranges for three example data points of a measurement for which the variance between repeated measures is the same regardless of their mean value (i.e. homoscedastic data such as that demonstrated in A).

The Coefficient of Variation is the standard deviation of the data, divided by the mean, multiplied by 100. It assumes a normal distribution, that the magnitude of error is proportional to the magnitude of the measure and can only be applied to ratio data with a true zero point. Each method has its benefits and pitfalls, but the LOA considers the greatest number of possible assumptions in the data of the measurements summarised above. There are a number of other methods (e.g. Ludbrook, 1997) but the use of these is not widespread in the sport or

clinical biomechanics literature and their application in the presence of heteroscedasticity has not been clearly demonstrated and may be complicated to implement (Mullineaux, Barnes and Batterham, 1999).

There is an additional challenge when applying these methods to time series data compared to discrete measurement values as was discussed above. Pini, Markstrom and Schelin (2019) highlighted that time series data is more frequently being used in place of extracting single values from a time series, but that there is little comment in sport science literature of how to best estimate the repeatability of time series. They compared seven approaches which included: functional limits of agreement, coefficient of multiple correlation, distance measures (the L_2-distance), a measure of similarity (a functional correlation) and pointwise calculations. The pointwise calculations applied statistical calculations that would normally be applied to discrete data points (e.g. Pearson correlations, Intra Class Correlations (ICC) and SEM) to each data point within a time series. Based on the analysis of a variety of simulated data sets, Pini, Markstrom and Schelin (2019) suggested that pointwise calculations of the SEM were the best performing measures of absolute reliability as they provided results over a time domain and could be integrated to provide a single summary statistic of absolute reliability for the curve. The authors recommended pointwise SEM indexes as descriptive indicators of absolute repeatability on the basis that they were straight forward to implement making them relevant for both researchers and sports coaches. The authors did however highlight the weaknesses of such an approach in that the information provided was purely descriptive and should not be used for inferential identification. Pini, Markstrom and Schelin (2019) also failed to recognise some of the assumptions of the ICC and SEM methods when applied to discrete data, in that they rely on normal distributions, and do not account for heteroscedasticity.

Repeatability of vector coding

Very little research has investigated the repeatability of coordination variability measures derived from vector coding. One study used the vector coding method first used by Heiderscheit, Hamill and van Emmerik (2002) to calculate trunk-pelvis coordination variability across a change of direction task in gait (Smith and Kulig, 2016). Coordination variability was averaged across the time series and four participants repeated the data collection three days after their first testing. The standard error of measurement measure of absolute reliability for the coordination variability measure was 0.23º (mean values were not reported in the study for the repeatability dataset to use as a reference, but similar data reported in the same article suggest a group mean of between 7.26° and 24.89°) and the authors concluded the measurement had excellent repeatability. As the only published research on

repeatability of a vector coding variability method, these findings are valuable. However, the sample population was small, the movement tested (turning during walking) has not commonly been investigated elsewhere and the specific coupling used was not relevant for the lower-limb musculoskeletal injuries which have commonly been associated with coordination variability. Thus, there is a real need for more thorough investigations of absolute reliability in coordination variability measures.

Relative reliability

In the same way that it is important to understand the repeatability of a measurement in order to assess changes within an individual, the ability of a measure to consistently rank participants over repeated measurements is important when comparing multiple populations or groups and the measurement of this is termed relative reliability.

Measurements of relative reliability

Several statistical techniques have been used to assess relative reliability such as correlation coefficients, intra class correlations and regression (Atkinson and Nevill, 1998). These measures of relative reliability are all affected by sample heterogeneity. Atkinson and Nevill (1998) recommend that reporting a relative reliability index can be useful as in indication of adequate relative reliability in a particular population but that it should not be the focus of a reliability study.

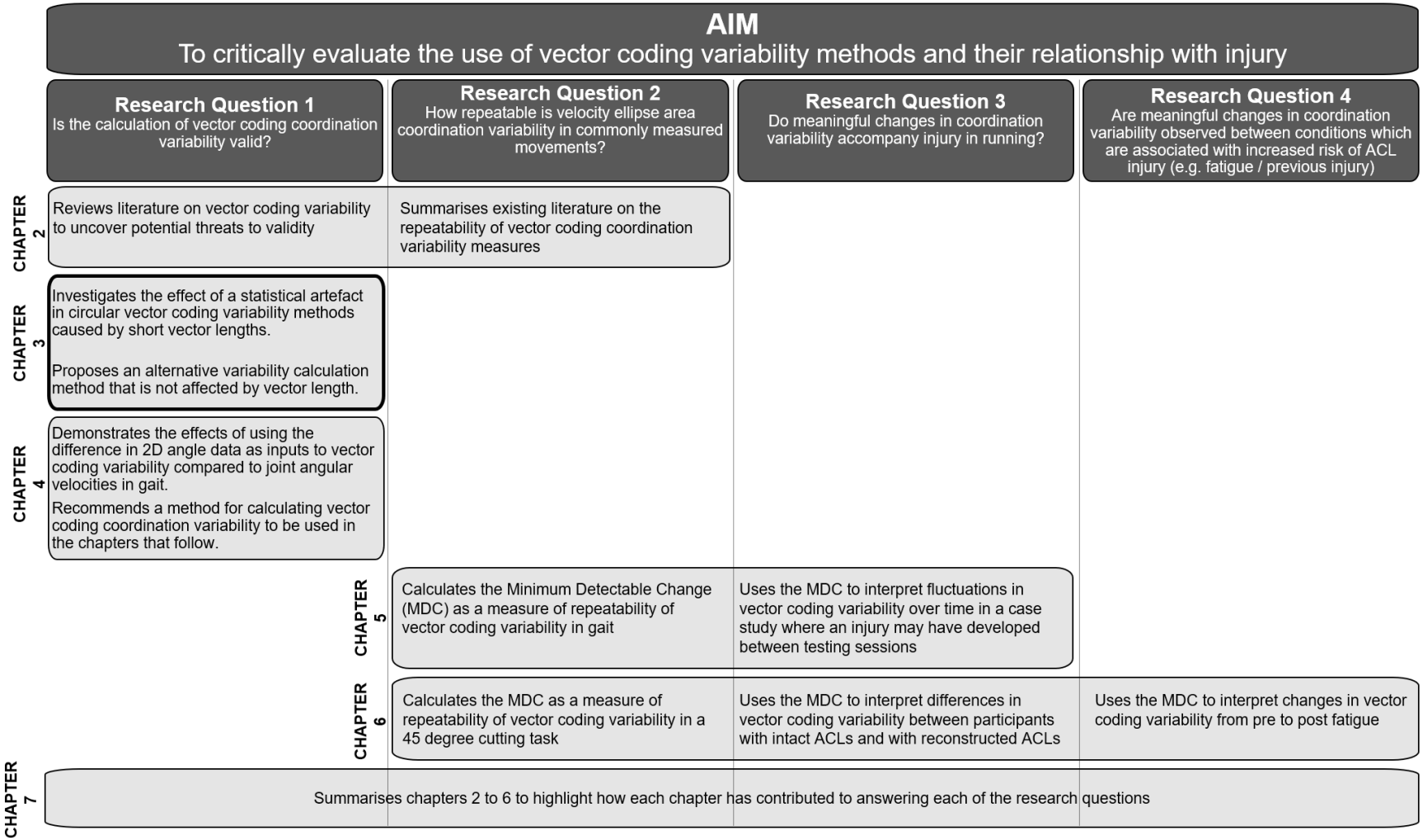
Relative reliability of vector coding

Within the vector coding coordination variability research, Smith and Kulig (2016) reported an ICC for trunk-hip coordination variability measured using the Heiderscheit, Hamill and van Emmerik (2002) method of 0.98 on a subsample of their population (n=4) whose joint kinematics were measured during a turning task on two occasions within 3 days of each other. An ICC of 0.98 is indicative of excellent reliability based on the ICC criteria set by Koo and Li (2016) but concerns have been raised about the ability of the ICC to determine adequate consistency of group positions (Atkinson and Nevill, 1998), it is not clear which ICC (of the 10 possible variants (Koo and Li, 2016)) was used in the study and therefore whether it was the correct choice and the turning task in which it has been measured is not common in the vector coding literature. Further research would be required to understand how measures of relative reliability can provide useful evidence to inform the measurement and interpretation of vector coding coordination variability. Given that relative reliability is affected by absolute reliability and the degree of heterogeneity of the sample (Atkinson and Nevill, 1998) the priority lies in first better understanding of the absolute reliability of coordination variability measures.

2.5 Gaps in the Literature

Variability in movement execution has become the focus of numerous research studies across a range of topics. This thesis will specifically address the research which has been conducted on the relationship between variability and musculoskeletal injury. Numerous methods exist to evaluate the magnitude and structure of variability and each of these methods measure different properties within the data. Relationships between musculoskeletal injury and variability have largely been investigated regarding the magnitude of variability, and within this, circular measures of coordination variability have been most popular. There is a body of evidence that has found coordination variability to be greater or lower in populations with musculoskeletal injuries but there has been little research to validate measures of coordination variability. Of note, it has been speculated that methods which measure variability using vector coding may be affected by the proximity of data points (Heiderscheit, Hamill and van Emmerik, 2002; Mullineaux, 2017).

In addition to unknowns related to the methods of measuring variability, there are also several unknowns regarding the mechanism by which coordination variability is related to injury. The first study that hypothesised that low variability could itself cause tissue damage recommended that prospective research would be required to investigate this further and understand how variability might affect injury or rehabilitation status. Since then, no prospective studies have been published that measure coordination variability and the onset of injury. Nor has any study investigated the absolute reliability of these measures, which would be valuable information for planning and interpreting longitudinal coordination variability data.


AIM
To critically evaluate the use of vector coding variability methods and their relationship with injury
Research Question 1
Is the calculation of vector coding coordination variability valid?
Research Question 2
How repeatable is velocity ellipse area coordination variability in commonly measured movements?
Research Question 3
Do meaningful changes in coordination variability accompany injury in running?
Research Question 4
Are meaningful changes in coordination variability observed between conditions which are associated with increased risk of ACL injury (e.g. fatigue / previous injury)
CHAPTER 2
Reviews literature on vector coding variability to uncover potential threats to validity
Summarises existing literature on the repeatability of vector coding coordination variability measures
CHAPTER 3
Investigates the effect of a statistical artefact in circular vector coding variability methods caused by short vector lengths.
Proposes an alternative variability calculation method that is not affected by vector length.
CHAPTER 4
Demonstrates the effects of using the difference in 2D angle data as inputs to vector coding variability compared to joint angular velocities in gait.
Recommends a method for calculating vector coding coordination variability to be used in the chapters that follow.
CHAPTER 5
Calculates the Minimum Detectable Change (MDC) as a measure of repeatability of vector coding variability in gait
Uses the MDC to interpret fluctuations in vector coding variability over time in a case study where an injury may have developed between testing sessions
CHAPTER 6
Calculates the MDC as a measure of repeatability of vector coding variability in a 45 degree cutting task
Uses the MDC to interpret differences in vector coding variability between participants with intact ACLs and with reconstructed ACLs
Uses the MDC to interpret changes in vector coding variability from pre to post fatigue
CHAPTER 7
Summarises chapters 2 to 6 to highlight how each chapter has contributed to answering each of the research questions

CHAPTER 3: APPLYING CIRCULAR STATISTICS CAN CAUSE ARTEFACTS IN THE CALCULATION OF VECTOR CODING VARIABILITY: A BIVARIATE SOLUTION

3.1 Introduction

Variability in human movement when repeating the same task is a certainty and can be attributed to different sources. Changes in the environment, physiological variation in sensory information and motor commands, and error in our ability to measure movement are all possible sources of variability (Preatoni et al., 2013). Physiological variation can be caused by errors (Harris and Wolpert, 1998) but some variation can have a positive effect on movement performance and can therefore be deemed functional. The functional component of movement variability might be beneficial to expert performance, motor learning, and injury prevention. For example, it can correct for errors which have already occurred (C. Button, Davids and Schollhorn, 2006), could allow an individual to select the best movement from exploring a range solutions (Newell et al., 1989), and may more evenly distribute loads between different tissues to prevent the accumulation of micro-trauma in one area (Hamill et al., 1999).

The body consists of multiple segments, which interact and coordinate with one another, therefore research on execution variability (i.e. the degree of inconsistency in how a movement is performed) has typically focused on variability in the coordination of movement rather than the variability of isolated joint or segment angle measurements. Coordination is an important aspect of human movement, but it is challenging to measure and quantify because it must reflect the movements of multiple individual components. Since the 1950s, angle – angle plots (also known as relative motion plots or cyclograms) have been utilised to graphically represent coordination between two segments or joints. The creation of coupling vectors between adjacent points on the angle – angle plot became termed ‘Vector Coding’ (Sparrow et al., 1987). Two methods of analysing the variability of the coupling vectors (and therefore the coordination between the angle – angle plot variables) were put forward and have appeared frequently in the literature since. The Tepavac Coordination Variability Method (TCVM) takes account of variation in both the length and direction of the coupling vector (Tepavac and Field-Fote, 2001). The Heiderscheit Coordination Variability Method (HCVM) focuses solely

on the variability of the coupling vector direction (Heiderscheit, Hamill and van Emmerik, 2002).

When performing the TCVM and HCVM on gait data, coordination variability is mostly low with sudden peaks (as shown in Figure 3.1A for the HCVM). This pattern was first observed by Heiderscheit, Hamill and van Emmerik (2002), where peaks in coordination variability in specific phases of the movement cycle were primarily explained as functional increases in variability that destabilised the dynamics of the system, thus facilitating a transition between coordination patterns. However, (Heiderscheit, Hamill and van Emmerik, 2002) also suggested the possibility of a statistical artefact by noting that the proximity of adjacent data points on the angle – angle plot (Figure 3.1B, C & D) may artificially affect the calculation of variability in the coupling vectors. The same observation has been reiterated elsewhere (Mullineaux, 2017) and the mathematical principle behind this statistical artefact has also been used to justify normalisation in the calculation of continuous relative phase (C. Button, Davids and Schollhorn, 2006). However, the extent to which the statistical artefact affects the HCVM and TCVM data has not been investigated further and has largely been overlooked by those publications which have used these analysis techniques. Therefore, the first aim of this work was to assess whether the HCVM and TCVM are contaminated by statistical artefact. The second was to propose a novel data analysis technique for the calculation of coordination variability, which is not susceptible to the statistical artefact. Treadmill running was used as a paradigmatic movement for the analysis.

3.2 Methods

Experimental and simulated approaches were utilised to investigate whether the HCVM and TCVM are subject to a statistical artefact. The experimental approach was used to inform a realistic range of coupling vector length inputs to the simulation and to indicate the potential effect of the statistical artefact on real data. The simulated approach identified the possible effect of the statistical artefact when both the signal and its possible variation were known *a priori*. A new bivariate method of calculating coordination variability is proposed based upon Mullineaux's bivariate approach (Mullineaux, 2017) that defines an ellipse from the coupling vector end points and calculates its area. The Ellipse Area Method was then applied to the experimental and simulated data and compared to the traditional coordination variability methods.

3.2.1 Experimental Data

The detailed data collection methods for the experimental data within this chapter are reported in greater detail in chapter 5.2.3 (page 100). In short: Twenty participants (10 male, 10 female)

were recorded running at 12 km/h on a treadmill (Powerjog JX100, Expert Fitness, UK) using a marker-based motion capture system operating at 200 Hz (Qualisys AB, Sweden). The study received ethical approval from the University of Bath, Research Ethics Approval Committee for Health, and all participants provided informed consent. An expert tester placed spherical,

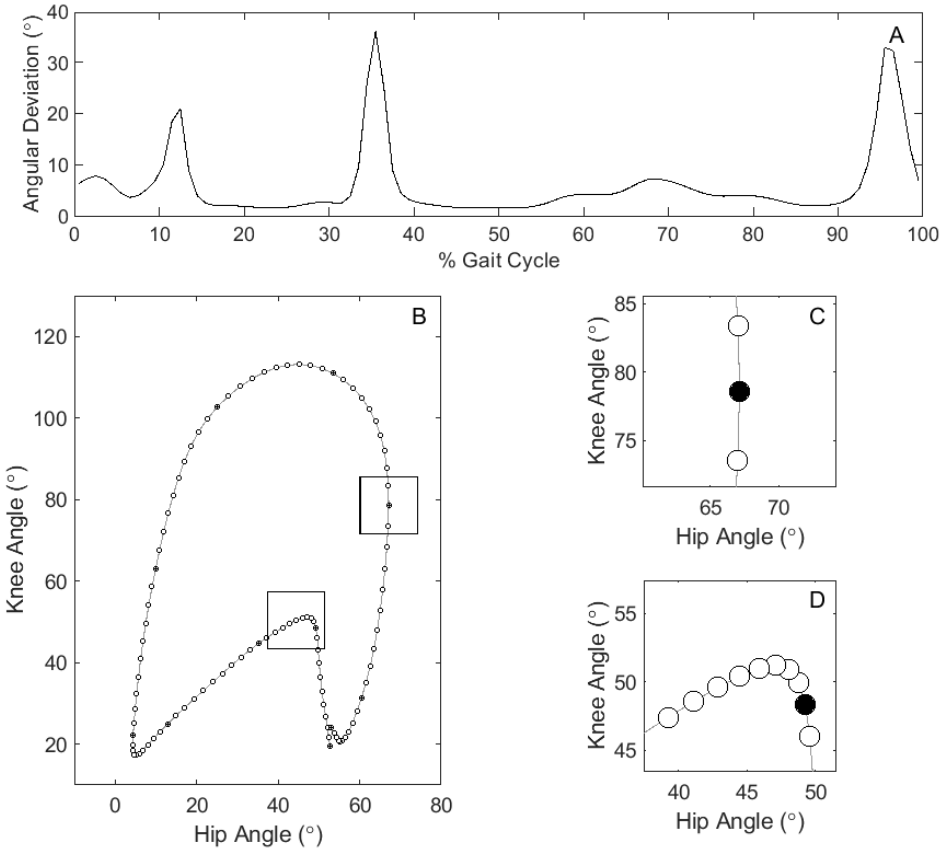


Figure 3.1. Possible evidence that an artefact related to the proximity of data points on angle – angle plots, first mentioned by Heiderscheit, Hamill and van Emmerik (2002) could be related to steep peaks observed in coordination variability data. A) Demonstration of the steep peaks observed in coordination variability calculated using the Heiderscheit, Hamill and van Emmerik (2002) coordination variability method B) An example of the angle – angle plot for the sagittal hip – knee coupling from a single gait cycle with two highlighted areas. Every tenth data point is filled. The higher highlighted area is magnified in C) and demonstrates a proportion of the curve where the distance between subsequent data points is much greater compared to the lower highlighted area that is magnified in D) where data points are very close together. The area highlighted in D represents 9-18% of the gait cycle and the area highlighted in C represents 79-81% of the gait cycle. The three highest peaks in A correspond to the three portions of time within B that the data points can be observed to be closest together (i.e. 9-18%, 30-40% and 90-100%)

retro-reflective markers (16 mm diameter) on the lower limbs and pelvis. The marker data were labelled and tracked in QTM and exported to Visual3D (V5, C-Motion, USA) where they were low-pass filtered with a cut-off of 8 Hz. Filtered trajectories were used to calculate joint angles for the hip, knee and ankle for all 3 joint rotations of the right leg. These data were

exported to MATLAB (Mathworks, Natwick, MA) where a validated kinematic ground-contact algorithm to identify gait events (i.e. Foot Contact Algorithm (Handsaker et al., 2016), +3.1 ms offset compared to force validation with confidence interval -11.8 to +18.1) was employed to identify 21 consecutive foot-strikes from the right leg, from which 20 gait cycles (*c*) of joint angle data were created (average stride duration: 142 (SD 7) frames). Each stride was temporally registered to 101 data points where $t = 1, \ldots 101$. Couplings were formed for all 36 possible combinations of joint and rotation couplings.

3.2.2 Simulation Data

The movement of two pendula (indexed as A and B) were modelled using publicly available code (Kolukula, 2011). Their reciprocal angular positions relative to the horizontal are described by an angle – angle plot with known features (Figure 3.4A). The inputs to the simulated pendulum were adjusted (Table 3.1) so that together, their angular dynamics contained a range of coupling vector lengths and directions (Figure 3.4A and B) representative of the range of coupling vector lengths measured from experimental data (Figure 3.3). Twenty exact repetitions of the pendula angular position signals were generated to represent multiple cycles ($c = 1, \ldots, 20$) of the simulated signal. One thousand time points were simulated ($t = 1, \ldots, 1000$) and θ_A and θ_B represented the angle that pendulum A and B made with the horizontal respectively. One thousand time points were simulated in order to obtain enough data to show a clear relationship between coupling vector length and coordination variability across the range of coupling vector lengths observed in the experimental running data.

Table 3.1. Simulation inputs used for generating pendulum A and pendulum B angle data.

	Pendulum A	**Pendulum B**
Acceleration due to gravity (kg·m·s^{-2})	17	17
Mass of the pendulum (kg)	2	4
Length of the pendulum (m)	6	1
Damping	0	0
Initial pendulum position (rad)	0.75	-0.75
Initial pendulum velocity (rad·s^{-1})	5	5
Frames per second	70	70

In experimental data, repeated cycles are not exact replicas due to variation in both the movement coordination and variation caused by measurement error. Here, the possible effect of small amounts of random variation added to the signal has been simulated. In order to do

this, random numbers (ε_A and ε_B) were generated from a normal distribution ($\mathcal{N}$) with mean 0 and standard deviation 0.25 degrees at each time point, for each cycle:

$$\varepsilon_A \sim \mathcal{N}(0, (0.25)^2) \tag{3.1}$$

$$\varepsilon_B \sim \mathcal{N}(0, (0.25)^2) \tag{3.2}$$

The time series ε_A and ε_B were added to the simulated pendula time-series signals (Equations 3.3 and 3.4). A standard deviation of 0.25 degrees was selected to represent a theoretical variation that caused a spread in data of no more than 1 degree at each time point.

$$\hat{\theta}_A = \theta_A + \varepsilon_A \tag{3.3}$$

$$\hat{\theta}_B = \theta_B + \varepsilon_B \tag{3.4}$$

3.2.3 Traditional Coordination Variability Methods

The HCVM (Heiderscheit, Hamill and van Emmerik, 2002) and TCVM (Tepavac and Field-Fote, 2001) were used to calculate coordination variability of the 20 repetitions of simulated pendulum data. The TCVM value was subtracted from 1 so that higher values represented greater coordination variability (Tepavac and Field-Fote, 2001) as is the case for the HCVM. Both the HCVM and TCVM have a minimum value of 0 but are capped at ~81° and 1 respectively.

3.2.4 Bivariate Ellipse Area Method

In the HCVM and TCVM the vectors created between adjacent data points on the angle – angle plot are effectively normalised to originate from the same point (Figure 3.2A-C). The variation in the angle that each vector makes with the horizontal is then calculated as a measure of coordination variability (HCVM) or as a component of the coordination variability measure (TCVM). In contrast, the bivariate ellipse area method forms an ellipse based on the end positions of each of the normalized vectors (Figure 3.2D). This provides a bivariate measure of variability that is affected by the direction and length of the coupling vectors. In the same way as the HCVM and the TCVM, the bivariate method is based on the coupling of two angle

signals: one is assigned as the x-component of the angle – angle diagram (θ_x) and another as the y-component (θ_y). Of note, for the purpose of calculating ellipse area it is not important which joint angle is displayed on the x or y axis of the angle – angle plot, but traditionally vector coding methods display the more proximal of the two components on the x axis (Hamill, McDermott and Haddad, 2000).

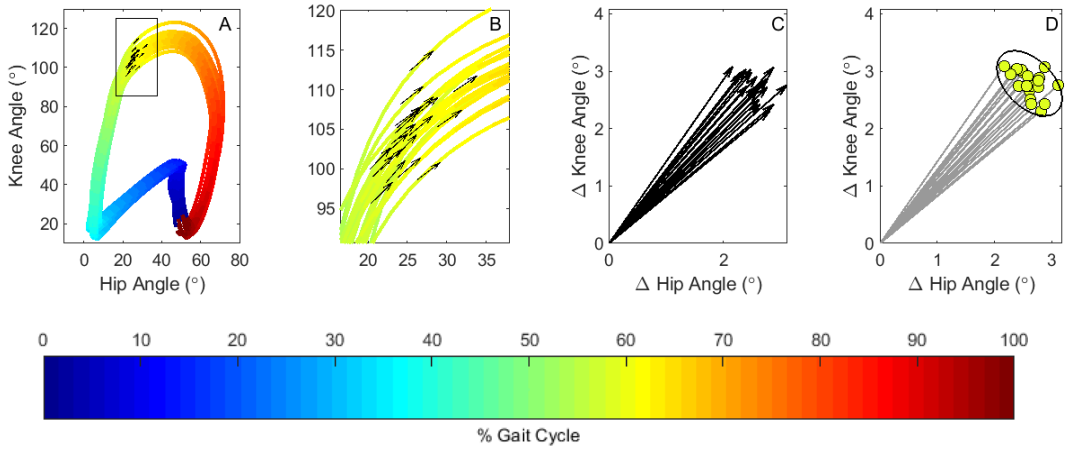


Figure 3.2. Example of how the ellipse area coordination variability method is calculated from an angle – angle diagram. A) Hip flexion/extension – knee flexion/extension angle – angle plot of 20 gait cycles. B) Magnification of time points from 59 to 60% of the time normalised gait cycle with vectors between these time points highlighted in black. C) Vectors highlighted in B normalised to the same starting point. D) Creation of ellipse around the 20 end points of the normalised ellipses.

In order to demonstrate the methods for calculating ellipse area from the original angle data, θ_x and θ_y have been used in the following equations. For the experimental data these represent the angle signals within a coupling pair that has been assigned as the x-axis component and y-axis component respectively, e.g. in the hip flexion/extension – knee flexion/extension coupling, hip flexion/extension is presented by θ_x and knee flexion/extension by θ_y. The same calculations were used to calculate ellipse area from the simulated data, but with $\hat{\theta}_A$ in place of θ_x and $\hat{\theta}_B$ in place of θ_y.

First, the change in angle ($\Delta\theta$) between adjacent data points was calculated for θ_x (Equation 3.5) and θ_y (Equation 3.6) for each movement cycle and participant, where *t* is the temporal index of that data:

$$\Delta\theta_{x_{t+0.5}} = \theta_{x_{t+1}} - \theta_{x_t} \quad (3.5)$$

$$\Delta\theta_{y_{t+0.5}} = \theta_{y_{t+1}} - \theta_{y_t} \quad (3.6)$$

The change in angle was indexed at the midpoint between the two temporal indexes from which it was calculated. Many vector coding methods index the change in angle as the first index of the data from which they are calculated (e.g. Heiderscheit, Hamill and van Emmerik, 2002) , but this causes a slight temporal advance in the data therefore the midpoint has been used throughout this programme of research when calculating the change in angle.

The ellipse was then defined using the same calculations as reported by Duarte and Zatsiorsky (2002), differing only in the determination of the size of the ellipse, where the chi-squared scaling factor (k, Equation 3.14) proposed by Mullineaux (2017) due to its independence of sample size was employed. In detail: the mean change in angle ($\overline{\Delta\theta}$) was calculated across the twenty simulated cycles (c) at each time point for $\Delta\theta_x$ and $\Delta\theta_y$:

$$\overline{\Delta\theta} = \frac{\sum_c^C \Delta\theta}{C} \tag{3.7}$$

The covariance matrix (K, $\begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{C} & \boldsymbol{D} \end{bmatrix}$) was then calculated at each time point across c stride cycles:

$$K = \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{C} & \boldsymbol{D} \end{bmatrix} \tag{3.8}$$

$$\boldsymbol{A} = \frac{1}{(n-1)\sum_c^C \left(\Delta\theta_{x_c} - \overline{\Delta\theta_x}\right)^2}$$

$$\boldsymbol{B} = \boldsymbol{C} = \frac{1}{(n-1)\sum_c^C \left(\Delta\theta_{x_c} - \overline{\Delta\theta_x}\right)\left(\Delta\theta_{y_c} - \overline{\Delta\theta_y}\right)}$$

$$\boldsymbol{D} = \frac{1}{(n-1)\sum_c^C \left(\Delta\theta_{y_c} - \overline{\Delta\theta_y}\right)^2}$$

The eigenvalues (λ) of covariance matrix K were defined by the formula:

$$0 = \det(K - \lambda I) \tag{3.9}$$

$$0 = \det\begin{bmatrix} \boldsymbol{A} - \lambda & \boldsymbol{B} \\ \boldsymbol{C} & \boldsymbol{D} - \lambda \end{bmatrix}$$

$$0 = (\boldsymbol{A} - \lambda)(\boldsymbol{D} - \lambda) - (\boldsymbol{B} \cdot \boldsymbol{C})$$

$$0 = \lambda^2 - (\boldsymbol{A} + \boldsymbol{D})\lambda + (\boldsymbol{A} \cdot \boldsymbol{D} - \boldsymbol{B} \cdot \boldsymbol{C})$$

and the coefficients to solve the roots of the quadratic formula in Equation 3.9 are therefore:

$$b = \boldsymbol{A} + \boldsymbol{D} \tag{3.10}$$

$$c = \boldsymbol{A} \cdot \boldsymbol{D} - \boldsymbol{B} \cdot \boldsymbol{C} \, . \tag{3.11}$$

The two eigenvalues λ_1 and λ_2 can therefore be calculated as:

$$\lambda_1 = \frac{b - \sqrt{b^2 - 4c}}{2} \tag{3.12}$$

and

$$\lambda_2 = \frac{b + \sqrt{b^2 - 4c}}{2} \tag{3.13}$$

A scaling factor, *k*, was calculated based on the probability, p = 0.95, that a future data point would lie within the defined ellipse from the inverse of the chi-squared cumulative distribution function for 2 degrees of freedom (Schubert and Kirchner, 2014; Mullineaux, 2017).

$$k = \sqrt{-2 \cdot \log_e(1 - p)} \tag{3.14}$$

The magnitudes of $\lambda_1$and λ_2 were scaled by *k* to give the magnitudes of the two ellipse axes (X_1 and X_2)*:*

$$X_1 = \mathrm{k} \cdot \sqrt{\lambda_1} \tag{3.15}$$

$$X_2 = \mathrm{k} \cdot \sqrt{\lambda_2}$$

The area of the ellipse, *V*, was calculated as:

$$V = \Pi \cdot X_1 \cdot X_2 \tag{3.16}$$

Coupling vector length (l) was calculated as the length of the hypotenuse of a right-angled triangle with sides $\Delta\theta_x$ and $\Delta\theta_y$ at each time point in each cycle:

$$l = \sqrt{(\Delta\theta_x)^2 + \left(\Delta\theta_y\right)^2} \tag{3.17}$$

and average coupling vector length ($\bar{l}$) was computed across the 20 cycles at each point in time:

$$\bar{l} = \frac{\sum_c^C l_c}{C} \tag{3.18}$$

3.3 Results

In the experimental running data, approximately 44% of all possible coupling vector lengths had a magnitude smaller than 1° which is reflected in the right-skewed distribution of the histograms (Figure 3.3A). The minimum coupling vector length across gait cycles observed in the experimental data was <0.05°, and the maximum length observed was 6.6°. In the simulated data, the minimum coupling vector length was <0.05° and maximum was 6.2°. Depending on the joint angle coupling selected, coupling vector length distributions varied (e.g. Figure 3.3B).

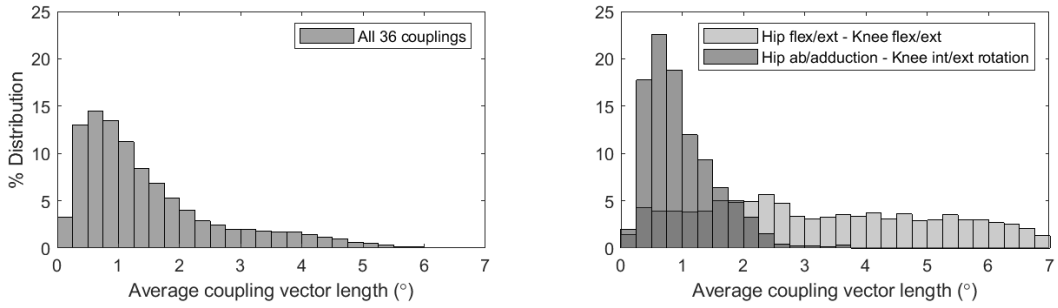


Figure 3.3. Normalised distributions of coupling vector lengths from experimental running data of all time points in the 20 stride cycles of the 20 participants. A) The distribution when all 36 joint couplings from the possible combination of tri-planar hip, knee and ankle rotations are considered together, and B) Examples of individual coupling distributions for hip ab/adduction – knee internal/external rotation (dark grey) and hip flexion/extension – knee flexion/extension (light grey) couplings. These couplings were chosen to demonstrate the diversity of distributions associated with different couplings. The same couplings demonstrated in (B) have also been used in coordination variability literature, e.g. (Samaan et al., 2015b) and (A. Brown et al., 2016).

In the simulated data, increases in coordination variability (*V*) were observed for both the HCVM (Figure 3.4D) and TCVM (Figure 3.4F) when the average length of the coupling vectors was lower (Figure 3.4B). The four highest peaks in V_{HCVM} and V_{TCVM} coincided temporally with the lowest troughs in average length of the coupling vectors (at 4, 36, 67 and 98% time points). The standard deviation of the V_{TCVM} signal expressed as a percentage of the possible range in that measure (0 - 1) was 12% compared to 10% for the V_{HCVM} (possible range of 0 – ~81°). The range of the V_{TCVM} signal expressed as a percentage of the possible range in that measure was 77% compared to 83% for the V_{HCVM}.

The statistical artefact in the estimation of coordination variability for coupling vectors of smaller magnitude was noticeable for both the HCVM and the TCVM (Figure 3.4C&E) but not for the Ellipse Area Method (Figure 3.4G). The HCVM curve stabilised at shorter vector lengths (Figure 3.4C) compared to the TCVM (Figure 3.4E).

Coordination variability measured using the TCVM is the product of variation in the angle and variation in normalized vector length. The variation in the angular component was shown to be less affected than in the HCVM (Figure 3.5C - *V* was relatively stable until average vector lengths reduce to less than 1.5° compared to Figure 3.4C). However, variation in vector length was also affected by the average coupling length (Figure 3.5D&E). The effect was less extreme (at the shortest average vector length the effect of vector length was only 60 % of the maximum range compared to >70% for angular dispersion and angular deviation), but the relationship continued across a greater range of vector lengths (i.e. *V* only appeared to stabilise around average vector lengths of 5°).

In the experimental data, steep rises in HCVM coordination variability (Figure 3.6B) coincided temporally with periods where the coupling vector length was shorter (Figure 3.6A). Some of the same peaks were observed in the Ellipse Area Method but they were less prominent in comparison to the rest of the signal (Figure 3.6B). Shortly before 80% of the gait cycle, an unusual feature can be observed in the ellipse area data (Figure 3.6B&C).

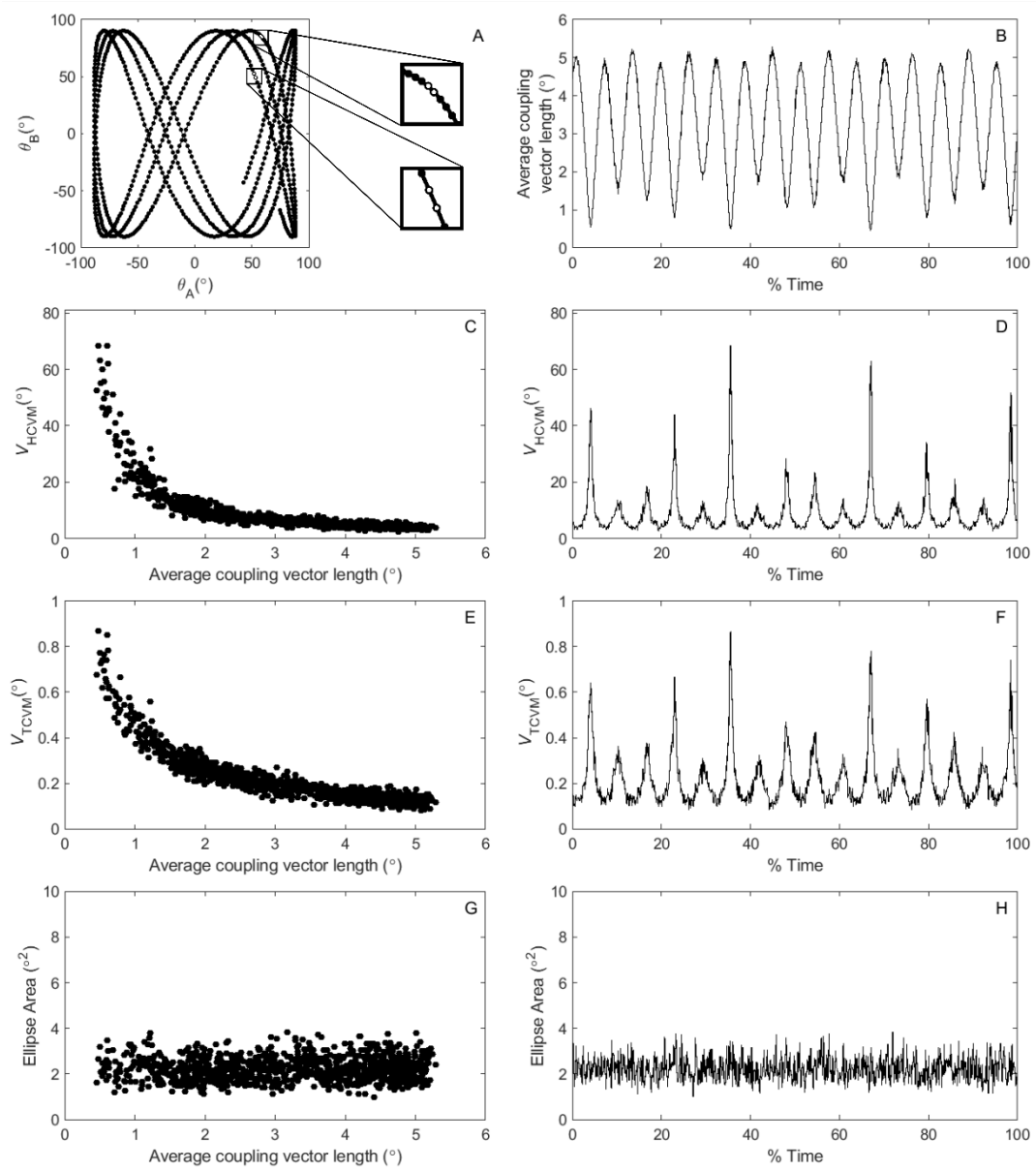


Figure 3.4. Pendulum simulation graphs for 1000 time points demonstrating the relationship between vector length and three measures of coordination variability. A) Angle – angle plot demonstrating variation in the coupling vector lengths between adjacent data points for the single pendulum simulation upon which the analysis is based. The longest coupling vectors are found on the straights and correspond to the peaks in Figure 1B. The shortest vectors occur around the turning points and correspond to the troughs in Figure 1B. B) Average coupling vector lengths from the 20 repetitions of the pendulum signal C) Relationship between the average coupling vector length and HCVM coordination variability. D) HCVM coordination variability. E) Relationship between the average coupling vector length and TCVM coordination variability. F) TCVM coordination variability. G) Relationship between the average coupling vector length and the ellipse method. H) Coordination variability from the newly proposed Ellipse Area Method.

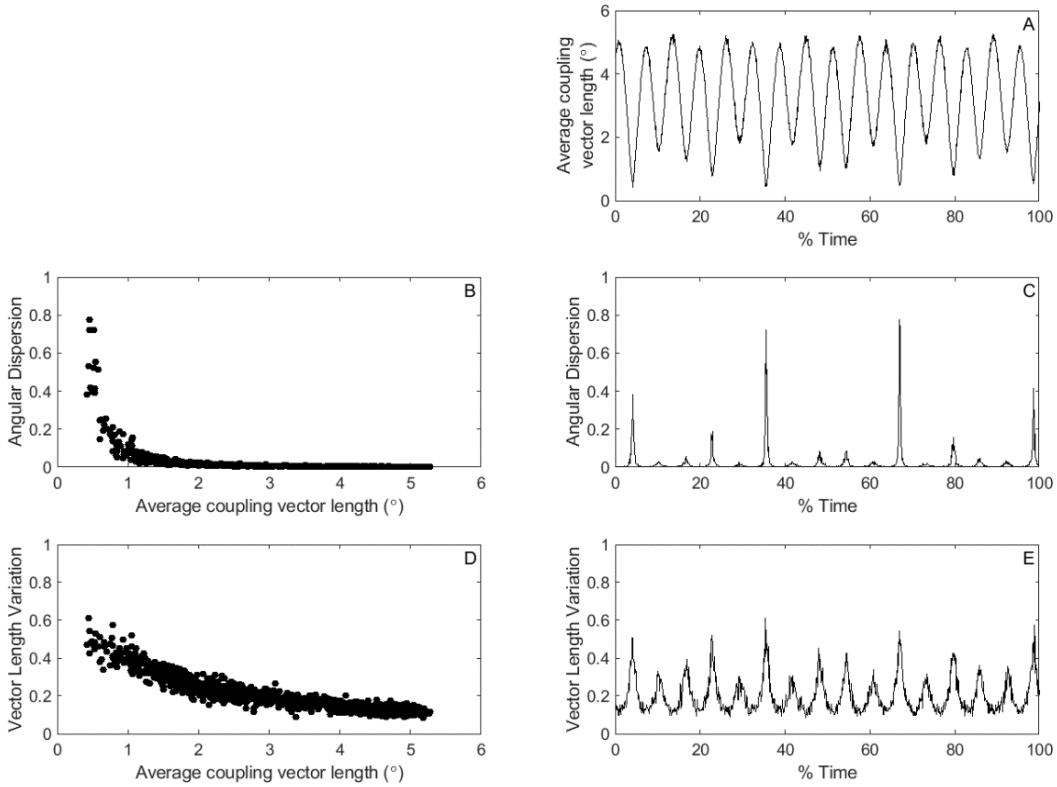


Figure 3.5. Pendulum simulation graphs for 1000 time points demonstrating the relationship between vector length and the two components of the Tepavac and Field-Fote (2001) vector coding coordination variability measure. A) Average coupling vector lengths calculated across 20 repetitions of the pendulum signal at each point in time. B) Relationship between the average coupling vector length and angular dispersion – the component of the TCVM that measures variation in the vector angles. The value has been subtracted from 1 so that high values represent greater variation in vector angle C) Angular dispersion. The value has been subtracted from 1 so that high values represent greater variation in vector angle. D) Relationship between the average coupling vector length and vector length variation – the component of the TCVM that measures variation in the vector angles. The value has been subtracted from 1 so that high values represent greater variation in vector length. E) Vector length variation. The value has been subtracted from 1 so that high values represent greater variation in vector length.

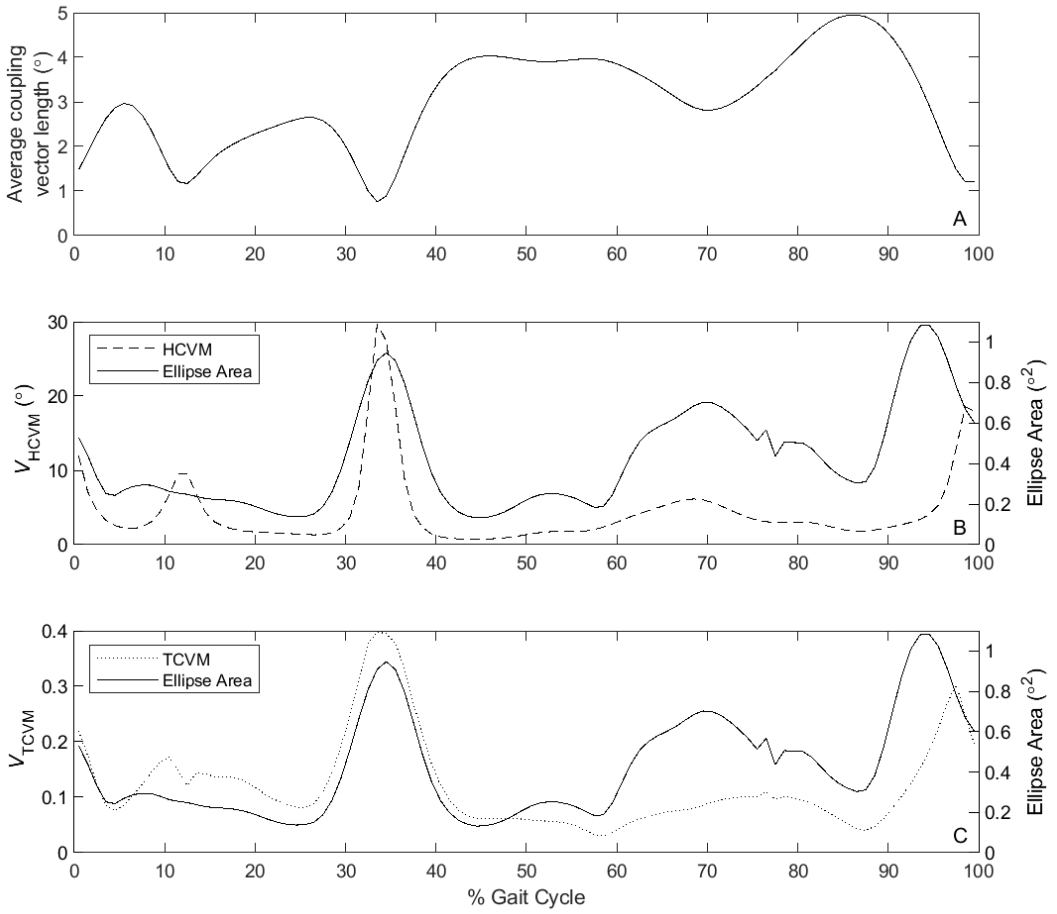


Figure 3.6. Example hip flexion/extension – knee flexion/extension coupling vector length and coordination variability from an individual participant during treadmill running at 12 km/h calculated from 20 stride cycles. A) Average coupling vector length. B) HCVM coordination variability (solid line) and Ellipse Area Method coordination variability method (dashed line). C) TCVM coordination variability (dotted line) and Ellipse Area Method coordination variability method (solid line).

3.4 Discussion

The aim of this chapter was to demonstrate whether a statistical artefact may affect the calculation of vector coding coordination variability using conventional approaches such as those first demonstrated by Heiderscheit, Hamill and van Emmerik (2002) (HCVM) and (Tepavac and Field-Fote, 2001) (TCVM). It has been demonstrated that when a pre-determined amount of variation was added to repetitions of the same simulated signal, steep peaks in coordination variability calculated using the HCVM and the TCVM are observed where a consistent variability output would be expected. These peaks (i.e. inflated variability) occurred when coupling vector lengths between data points on the angle – angle plot were shorter. This is suggestive of a statistical artefact associated with the use of circular statistics when there are varying vector lengths. The shorter coupling vector lengths, which were

associated with the statistical artefact, were also demonstrated to be prevalent in experimental data similar to that upon which these analyses are commonly performed. As a possible solution to the reported limitations of existing methods, the Ellipse Area Method was proposed; a bivariate measure of spread that has been demonstrated to be unaffected by coupling vector length.

In the simulated data where the variation in the signal was pre-defined, steep rises were seen in CV calculated using the HCVM and TCVM (Figure 3.4D and 1F). These coincided temporally with the shortest coupling vectors (Figure 3.4B). The relationship between CV and coupling vector length when the coupling vectors were shorter was clearly non-linear (Figure 3.4C&E) indicating the presence of the statistical artefact for the HCVM and TCVM. No relationship was apparent between the Ellipse Area Method and coupling vector length (Figure 3.4G). Comparing the HCVM and TCVM, coordination variability stabilised at shorter coupling vector lengths in the HCVM (Figure 3.4C) than in the TCVM (Figure 3.4E). Furthermore, the fluctuations in the simulated coordination variability calculated using the TCVM (Figure 3.4F) were less pronounced in relation to the possible range of the signal at the shortest average coupling vector lengths but more pronounced at longer average vector lengths when compared to the HCVM (Figure 3.4D). This observation can be explained by examining the two components (direction variability and length variability) of the TCVM (Figure 3.5). Previous literature had questioned whether the proximity of data points on the angle-angle plot (i.e. the vector length) might affect the angular deviation (Heiderscheit, Hamill and van Emmerik, 2002; Mullineaux, 2017) but the simulation results also indicated that variation in normalized vector length increased with shorter vector lengths. The combined effects of the effect of vector length on the angular dispersion and the normalized vector length variation explain the relationship between coordination variability measured using the TCVM.

The principle which causes the statistical artefact in the HCVM and angular component of TCVM lies in the treatment of these data as circular. If the variability of coupling vectors on the angle – angle plot are analysed with circular statistics, it must be accepted that if the variation of the data causes the spread of coupling vector end points to be centred round the origin, then the angular dispersion (used in TCVM) and angular deviation (HCVM) will approach their respective maximum values. The same linear variation in abscissa and ordinate coordinates of the coupling vector end points not centred about 0 will have a lower angular deviation (Figure 3.7A). This is regulated by a non-linear relationship, similar to that displayed in Figure 1C. Regardless of whether the variation in the data is only small, as was simulated in this paper, or larger, as may be the result of actual variation in the movement performance, the use of circular statistics elicits a non-linear relationship between coupling vector length and angular deviation. This characteristic of circular statistics in the presence of varying vector

lengths has a direct effect on the calculation of coordination variability using the HCVM and TCVM and is most likely to occur when coupling vector lengths are shorter.

The relationship between normalised vector length variation and average vector length had not been foreseen when this research was initiated. The absolute variation in the vector lengths was constant within the randomly simulated noise. However, the normalisation process of the TCVM divides by maximum vector length (Tepavac and Field-Fote, 2001), and maximum vector length increased linearly with average vector length. This resulted in a reciprocal like relationship, similar to that which was observed (Figure 3.5D).

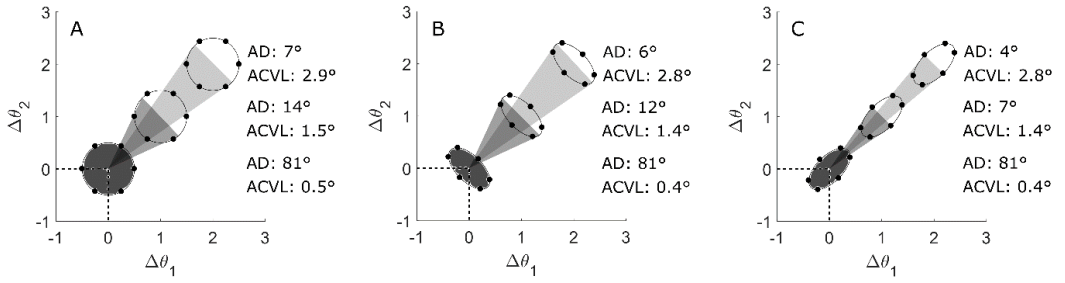


Figure 3.7. The effect of the average coupling vector length (ACVL) on angular deviation (AD) when variance in the $\Delta\boldsymbol{\theta_1}$ (abscissa) and $\Delta\boldsymbol{\theta_2}$ (ordinate) coordinates are equal. (A), and when the main axis of variation in the bivariate data is perpendicular (B) and parallel (C) to the average coupling vector. On each plot, circles/ellipses represent three separate average length scenarios that are demonstrated independently of each other (i.e. they are not consecutive time points). Each dot represents the end point of a coupling vector that has been normalised to have its origin at (0,0). Shaded areas are visual representations of the angular variation, which is maximal (~81°) when the coupling vectors are spread about the origin (dark grey), but is smaller if vector end points are offset from the origin (mid grey) and smaller again when vector end points are far away from the origin (light grey). Within each figure the AD is very different in the three ACVL scenarios but the circle/ellipse areas around the coupling vector end points are constant.

Possible solutions to the vector length artefact might have been to correct for the relationship or to discount data that was under a certain coupling vector length threshold (e.g. starting from the relationships in Figure 3.4C and 1E). The limiting factor with such approaches is that the relationship between coupling vector length and coordination variability is moderated by the magnitude of the variation in the data at each time point, which is difficult to model and likely impossible to predict a priori. In this paper the simulated variation had a SD of ~0.25 but variation in real data may increase or decrease over the course of the movement. The statistical artefact was still apparent when the simulation was run with different magnitudes of variation added to the pendulum signal. However, the coupling vector length threshold under which the statistical artefact dominated, increased when the variation was greater (Figure 3.8). Thus, with different variations in the data at each part of the signal, it is challenging to define a consistently valid threshold for a coupling vector length under which it can be confidently

stated the result is dominated by the statistical artefact. In addition to this, the simulation presented in this chapter modelled a situation where the variance in the abscissa and ordinate components of the angle – angle plot were equal. In reality, unequal variances can and will occur in ways that are currently impossible to predict, which adds another layer of complexity to the problem. If the main axis of variation at one time point across multiple cycles is perpendicular to the average vector, the effect of the statistical artefact is high. This decreases as the axis of variation becomes parallel to the mean vector (Figure 3.7B-C). This consideration makes both understanding whether data are affected by the statistical artefact and the possibility of applying a correction to the HCVM and TCVM yet more complicated and reinforces the need of a more robust estimator of coordination variability. Artificially increasing vector length would also be ineffective, as it would proportionally increase the variation in the data leaving the statistical artefact unchanged.

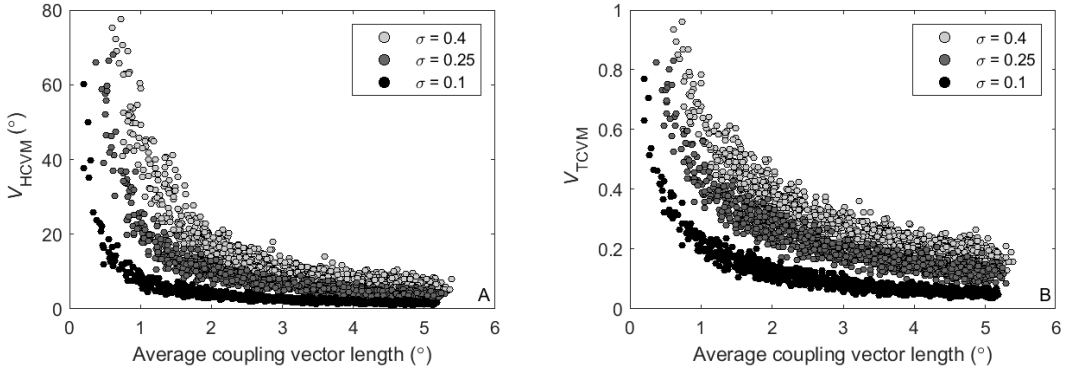


Figure 3.8. The relationship between coordination variability and average coupling vector length with different magnitudes of error. Three standard deviations (σ = 0.10° (black), σ = 0.25° (dark grey) and σ = 0.40° (light grey)) were used to generate the normal distribution from which random error was sampled and added to the simulated pendulum angle signals (Equations 3.1-3.4). Coordination variability was then calculated from these data and plotted against the averaging coupling vector length using the A) Heiderscheit Coordination Variability Method and B) Tepavac Coordination Variability Method.

The combination of simulated and experimental data presented in this chapter suggested that experimental data has the strong potential to be affected by statistical artefact, but it is difficult to quantify its effect. Looking at the running data in more detail, the steep rises in coordination variability coincided temporally with periods where the coupling vector length was shorter (Figure 3.6), which could be indicative of contamination of the coordination variability signal due to the statistical artefact. The statistical artefact appeared to be problematic in the data presented in this chapter, but the severity of its effect is ultimately dependent on the coupling vector length and the characteristics of the variation in the data. Therefore, the phase of the movement studied, the coupling that was analysed, the number of data points signals were time registered to, and the participant and movement in question can all affect the magnitude

of the statistical artefact. In the data, the shortest coupling vectors often coincided with times when one or both of the component variables of the coordination coupling changed direction (e.g. when a joint moves from flexion to extension). Thus, if an analysis of coordination variability were to focus on a period of the movement where a change in joint motion occurred, then the statistical artefact would likely have a greater influence on the outcome than if the average of the entire gait cycle were taken. Shorter vectors were also more likely throughout the signal when one or both of the component variables of the coordination coupling had a small range of motion. Considering the many factors that can impact upon the coupling vector length, researchers using the HCVM and TCVM for the assessment of coordination variability should investigate their own data to understand the possible effect of the artefact or consider other methods of analysing coordination variability.

As an alternative to considering angle – angle plot data as circular, Mullineaux (2017) recently suggested a bivariate approach to analyse differences between angle – angle plots. In a similar vein, bivariate statistics may be appropriate for the analysis of coordination variability. The ellipse method accounts for variability in both the length and direction of the coupling vectors, comparable to the TCVM. It has been demonstrated that the Ellipse Area Method is unaffected by coupling vector length (Figure 3.4G &H). This feature makes the method suitable for future investigations into coordination variability as it negates the need to understand and account for the complex nature of the statistical artefact associated with using circular statistics.

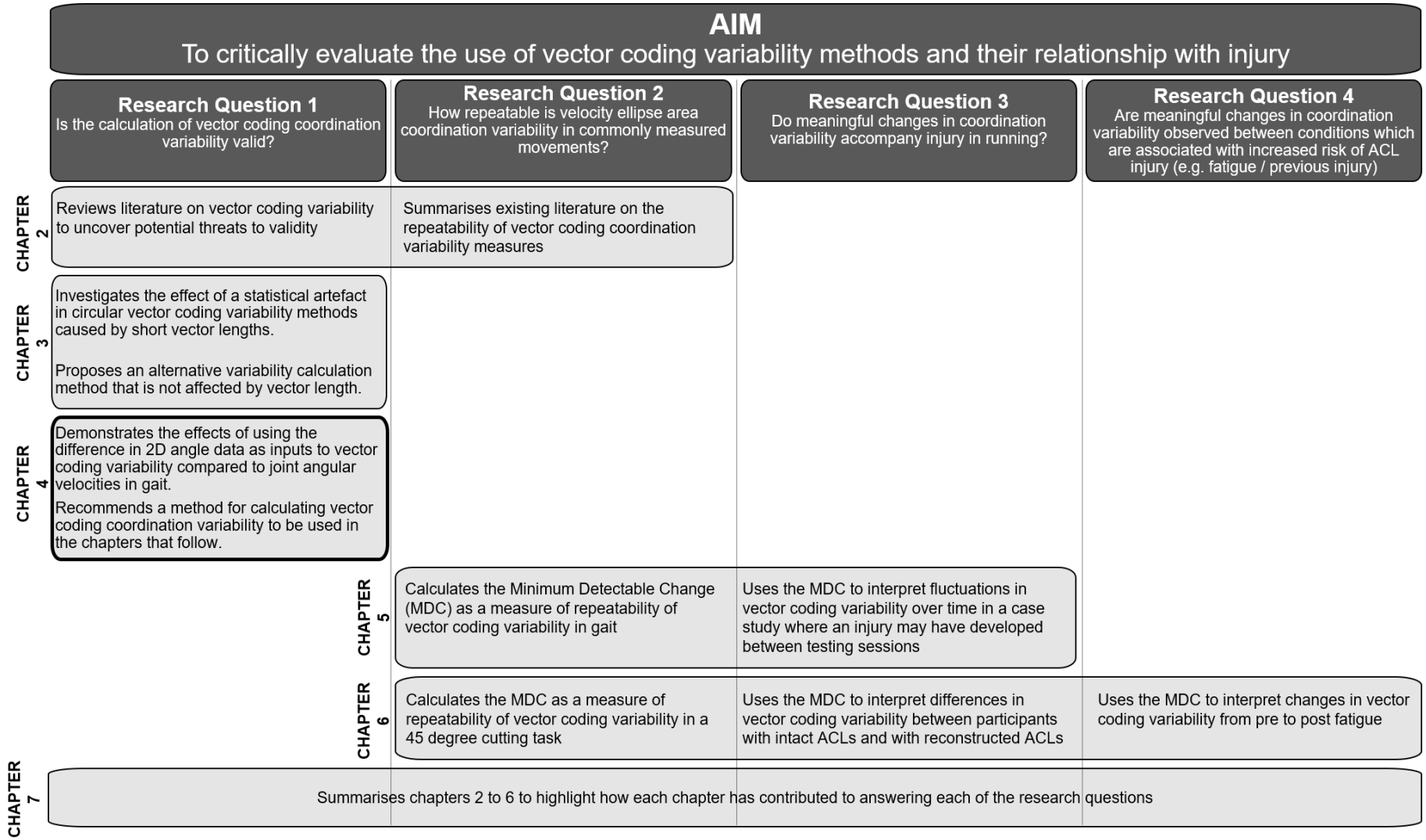
To demonstrate the Ellipse Area Method further, the method was applied to experimental data from a single participant and compared the results to those from the HCVM and TCVM (Figure 3.6B&C). Some of the signal's pattern was maintained so increased coordination variability was often observed when the joint movement reversed as was highlighted by Heiderscheit, Hamill and van Emmerik (2002) with the suggested explanation that increased variability supported the transition between coordination patterns. However, the effect was not consistent across the signal and it is not known how the magnitude of the signal peaks resulting from the use of circular statistics might have influenced the statistical outcome of this study and all those that have followed using the HCVM and TCVM. It is possible that the peaks caused by the statistical artefact in the HCVM and TCVM may have detracted attention from other features in the data and so these features became more apparent when the Ellipse Area Method was used. In the example provided (Figure 3.6B&C) an unusual feature was also observed in the ellipse area data which did not match the smoothness seen in the rest of the time series. Further work is required to better understand the ellipse area method as a measure of coordination variability and as an initial step towards this, the source of the unusual feature observed in Figure 3.6B&C will be investigated in more detail in Chapter 4.

3.5 Conclusion

This chapter has investigated the statistical artefact affecting popular biomechanical techniques that quantify coordination variability. The simulated data results demonstrated that when circular statistics are employed to calculate coordination variability, a statistical artefact can substantially inflate coordination variability values at shorter coupling vector lengths. The experimental data showed that coupling vector lengths where the statistical artefact is high, can be common in experimental gait data. Thus, future studies should not use methods based on circular statistics without investigating the possible impact of the statistical artefact on their results and conclusions. As a solution to the statistical artefact, an alternative method for calculating coordination variability was proposed. This bivariate approach was shown to be robust to the presence of different coupling vector lengths. An initial example of this method has been presented that may form a new basis for vector coding coordination variability research. Though the bivariate method appears to be a viable replacement for measuring coordination variability, it is important to note that some previous findings, which suggest the importance of coordination variability, are based on results from HCVM and TCVM methods. It may therefore be prudent to confirm these findings remain unchanged in light of this new evidence regarding the methods used to calculate them.

In conclusion, this chapter has highlighted a possible longstanding issue with current vector coding measures of coordination variability (specifically the HCVM and TCVM) bringing into question the validity of these techniques for measuring coordination variability in the presence of short vector lengths. The chapter has also provided additional evidence for an alternative method that is robust to differences in vector length and may therefore prove a more valid technique for continuing research on this topic. Together these findings have contributed new information to the research field about the validity of vector coding coordination variability calculations, addressing the first research question of this thesis – 'Is the calculation of vector coding coordination variability valid?'.

The next chapter will build on the work presented within this chapter by further exploring the validity of vector coding coordination variability. Specifically, it will investigate the effect of calculating the differences in two-dimensional angle time series to represent the dynamics of the system in comparison to the use of angular velocities. In doing this, the source of the unusual feature in the ellipse area data identified in this chapter is explained. Finally, this leads to the suggestion of a modification to the ellipse area method presented in this chapter for calculating vector coding coordination variability.


AIM
To critically evaluate the use of vector coding variability methods and their relationship with injury
Research Question 1
Is the calculation of vector coding coordination variability valid?
Research Question 2
How repeatable is velocity ellipse area coordination variability in commonly measured movements?
Research Question 3
Do meaningful changes in coordination variability accompany injury in running?
Research Question 4
Are meaningful changes in coordination variability observed between conditions which are associated with increased risk of ACL injury (e.g. fatigue / previous injury)
CHAPTER 2
Reviews literature on vector coding variability to uncover potential threats to validity
Summarises existing literature on the repeatability of vector coding coordination variability measures
CHAPTER 3
Investigates the effect of a statistical artefact in circular vector coding variability methods caused by short vector lengths.
Proposes an alternative variability calculation method that is not affected by vector length.
CHAPTER 4
Demonstrates the effects of using the difference in 2D angle data as inputs to vector coding variability compared to joint angular velocities in gait.
Recommends a method for calculating vector coding coordination variability to be used in the chapters that follow.
CHAPTER 5
Calculates the Minimum Detectable Change (MDC) as a measure of repeatability of vector coding variability in gait
Uses the MDC to interpret fluctuations in vector coding variability over time in a case study where an injury may have developed between testing sessions
CHAPTER 6
Calculates the MDC as a measure of repeatability of vector coding variability in a 45 degree cutting task
Uses the MDC to interpret differences in vector coding variability between participants with intact ACLs and with reconstructed ACLs
Uses the MDC to interpret changes in vector coding variability from pre to post fatigue
CHAPTER 7
Summarises chapters 2 to 6 to highlight how each chapter has contributed to answering each of the research questions

CHAPTER 4: ANGULAR DYNAMICS IN VECTOR CODING

4.1 Introduction

Vector coding measures of coordination were first suggested by Sparrow et al. (1987) and involve the creation of vectors between adjacent data points on angle – angle plots (also known as relative motion plots or cyclograms). The vectors represent the dynamics of the system and vector coding has since provided the basis of several techniques for analysing coordination (e.g. Hamill, McDermott and Haddad, 2000; Heiderscheit, Hamill and van Emmerik, 2002; Chang, van Emmerik and Hamill, 2008) and coordination variability (Hamill, McDermott and Haddad, 2000; Tepavac and Field-Fote, 2001; Stock et al., 2018; Mulloy et al., 2019). All of the techniques listed share a common basis that their inputs came from calculating the difference (Δ) between consecutive data points (in a time series indexed by *t*) in an angle signal (θ, Equation 4.1).

$$\Delta\theta_{t+0.5} = \theta_{t+1} - \theta_t \tag{4.1}$$

By extracting information that details the change from one data point to the next, $\Delta\theta$ contains information about the dynamics of how θ changes over time. More commonly, dynamics are represented by differentials with respect to time and it follows suit that the calculation of $\Delta\theta$ is similar to the numerator component of the central finite difference method (Equation 4.2) commonly used in biomechanical calculations (Winter, 2009).

$$\dot{\theta}_t = \frac{\theta_{t+1} - \theta_{t-1}}{2 \cdot \Delta t} \tag{4.2}$$

The central finite difference method is commonly used to approximate the derivate of vector quantities (Winter, 2009). In calculating the dynamics of vectors, each plane of motion is considered independent of the other. For example, to calculate the vertical velocity of an object, one only needs to know how vertical position changes with respect to time. In the vector coding scenario, the joint or segment angle inputs are not vector quantities but are Euler angle components. Biomechanical definitions state that the angular velocity of one Euler angle component is affected by the angular positions and dynamics of other Euler angle components (Equation 4.3).

$$\begin{bmatrix}\omega_X\\ \omega_Y\\ \omega_Z\end{bmatrix} = \begin{bmatrix}\dot{\theta}_X + \sin(\theta_Y)\cdot\dot{\theta}_Z\\ \cos(\theta_X)\cdot\dot{\theta}_Y - \sin(\theta_X)\cdot\cos(\theta_Y)\cdot\dot{\theta}_Z\\ \sin(\theta_X)\cdot\dot{\theta}_Y + \cos(\theta_X)\cdot\cos(\theta_Y)\cdot\dot{\theta}_Z\end{bmatrix} \quad (4.3)$$

*** (Winter, 2009) where X, Y, and Z represent the three axes of rotation about the proximal segment's reference frame.**

This presents a scenario where for a given rotation (X, Y or Z), $\Delta\theta$ can be considered an approximation of the correct angular dynamics (ω) via the similarity and association between $\Delta\theta$ and $\dot{\theta}$. The $\Delta\theta$ and ω outputs cannot be directly compared as they are measured in different units ($\Delta\theta$ in °, and ω in °·s^{-1}) but it is possible to compare if $\Delta\theta$ is proportional to ω when each method is applied to the same joint angle data. There are conditions when both methods will represent the same relative changes in the joint angle dynamics. For example

$$\omega_X = \dot{\theta}_X \propto \Delta\theta_X \quad \Leftrightarrow \sin\theta_Y = 0 \ \vee \ \dot{\theta}_Z = 0\,, \quad (4.4[1])$$

$$\omega_Y = \dot{\theta}_Y \propto \Delta\theta_Y \quad \Leftrightarrow \left(\sin\theta_X = 0 \ \vee \cos\theta_Y \ \vee \ \dot{\theta}_Z = 0\right) \ \wedge \quad (4.5)$$

$$\cos\theta_X = 1$$

and

$$\omega_Z = \dot{\theta}_Z \propto \Delta\theta_Z \quad \Leftrightarrow (\cos\theta_X = 1 \ \vee \cos\theta_Y = 1) \ \wedge \quad (4.6)$$

$$\left(\sin\theta_X = 0 \ \vee \ \dot{\theta}_Y = 0\right)$$

but there are also many scenarios when $\Delta\theta$ is not proportional to its ω counterpart in the same axis of rotation. For example in Equation 4.4 if $\sin\theta_Y \neq 0 \ \wedge \ \dot{\theta}_z \neq 0$ the quality of the $\Delta\theta_X$ approximation of ω_X can vary from good (when $\sin\theta_Y$ and $\dot{\theta}_Z$ are very close to zero) to poor (when $\sin\theta_Y$ is close to one and $\dot{\theta}_Z$ is large). The number of possible permutations is hypothetically infinite therefore it is important to understand how accurate the approximation is for specific datasets according to the range of angles and angular dynamics present in that data set.

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[1]
- $\propto$ Is proportional to
- $\Leftrightarrow$ If and only if
- $\vee$ Logical Or
- $\wedge$ Logical And

There are additional differences between $\Delta\theta$ and ω in the temporal information that is retained. Vector coding coordination variability methods have typically time normalised angle signals (θ) to modify multiple repetitions of a movement cycle (that have varying lengths) so that they all contain the same number of temporally normalised data points. These temporally normalised angle signals are then used to calculate $\Delta\theta$ (e.g. Tepavac and Field-Fote, 2001; Heiderscheit, Hamill and van Emmerik, 2002). As a result, data that is temporally diverse (e.g. Figure 4.1A) is manipulated by temporal normalisation in a way that temporal diversity between cycles is removed (e.g. Figure 4.1C). The coordination variability method first demonstrated by Heiderscheit, Hamill and van Emmerik (2002) has therefore been suggested to be void of temporal information (Hamill, McDermott and Haddad, 2000) as it only measures the ratio of change in one component of the coordination coupling compared to the other via a coupling angle. An absence of temporal information has been presented as a potential disadvantage of the vector coding approach in contrast to continuous relative phase methods where angular velocities are part of the input to the calculation process (van Emmerik, Miller and Hamill, 2014). In reality, the coordination variability calculation methods used by Heiderscheit, Hamill and van Emmerik (2002) and Tepavac and Field-Fote (2001) are influenced by temporal information (as was demonstrated in Chapter 3 by the presence of a statistical artefact when vector lengths were short). The method proposed by Tepavac and Field-Fote (2001) also contains temporal information by considering variation in the length of the vectors. By using an ellipse area methodology that uses angular velocities in place of $\Delta\theta$ as its input however, more temporal information is retained in the coordination variability measure, without the unpredictability of the artefact discussed in chapter 3..

Consequently, the aim of this study was to compare and contrast the possible advantages and disadvantages of using the traditional $\Delta\theta$ input in comparison to angular velocities (ω) for the calculation of coordination variability using the ellipse area method. The comparison will be based on theoretical and practical considerations but also draw from experimental data examples. The outcome will inform the method which will be used in the remaining thesis chapters.

4.2 Methods

4.2.1 Data Collection

Full details for the methods used to collect the experimental data presented within this chapter are provided in Chapter 5, Section 5.2.3 (page 100). A brief summary is reported here for convenience: Twenty participants (10 male, 10 female) were recorded running at 12 km/h on a treadmill (Powerjog JX100, Expert Fitness, UK) using a marker-based motion capture system operating at 200 Hz Qualisys, AB Sweden). The study received ethical approval from

the University of Bath, Research Ethics Approval Committee for Health, and all participants provided informed consent. An expert tester placed retro-reflective spherical markers (16 mm diameter) on the lower limbs and pelvis.

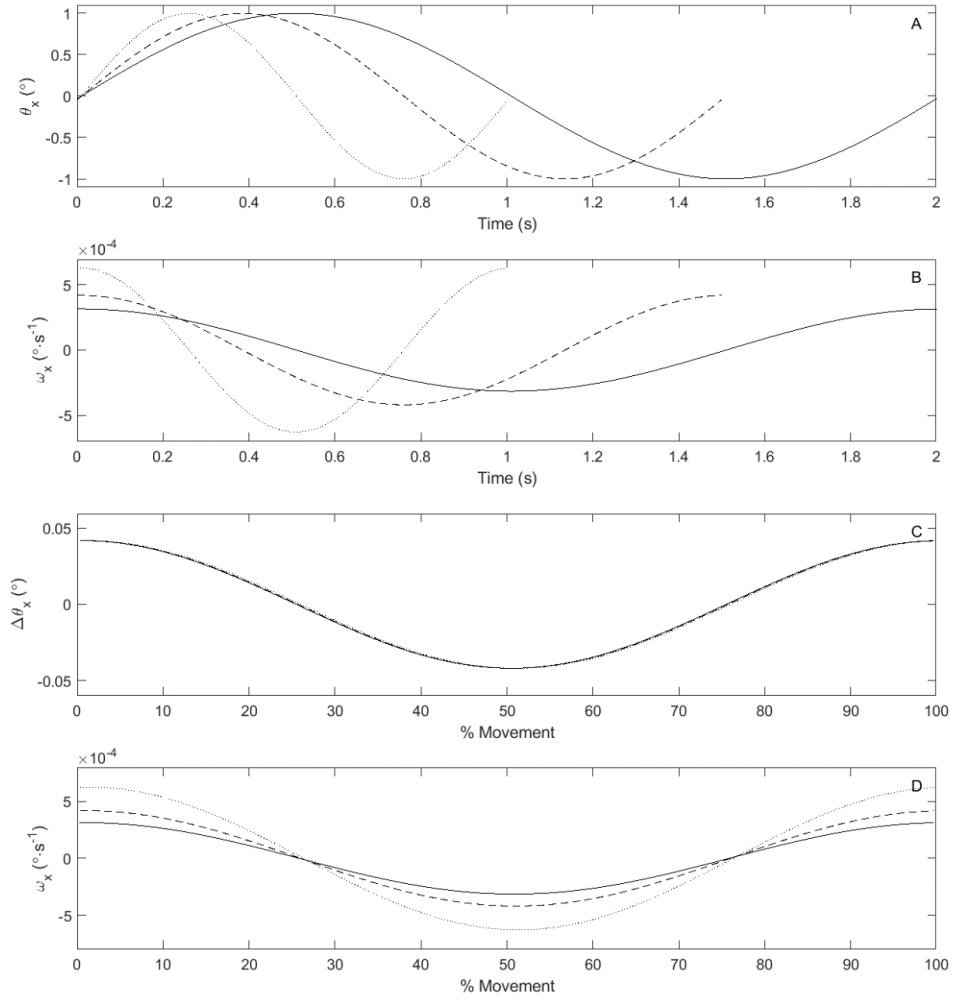


Figure 4.1. Differences in the temporal information retained when using angular velocities compared to time normalised changes in angle. A) Simulated example of an angle signal (θ, in this case a sine wave) with three different lengths to represent three exact repetitions of a movement at different speeds (slow – solid, medium paced – dashed, and fast – dotted) B) The respective angular velocities of each simulated movement repetition using the same line style conventions as in A calculated using Equation 4.2 C) The change in θ between temporally normalised time points of the three signals shown in A calculated using Equation 4.1. N.B. Δθ is the same for all three repetitions hence the appearance of a single line D) The temporally normalised angular velocity of the data shown in B, derived from the angle signals shown in A. Together the plots demonstrate that the dynamics of the three movements are represented differently when Δθ is calculated after temporal normalisation has occurred compared to when the dynamics of the three movements are represented by angular velocities. In this example differences in signal length have been exaggerated to demonstrate the concept and are not necessarily realistic.

4.2.2 Data Processing

The marker data were labelled and tracked in QTM (Qualisys AB, Sweden) and exported to Visual3D (V5, C-Motion, USA) where they were low-pass filtered with a cut-off of 8 Hz.

Filtered trajectories were used to calculate joint angles and angular velocities for the hip, knee and ankle of the right leg. These data were exported to MATLAB (Mathworks, Natwick, MA) where a validated kinematic ground-contact algorithm to identify gait events (Handsaker et al., 2016) was employed to identify 21 consecutive foot-strikes from the right leg, from which 20 strides of joint angle data were created (average stride duration: 142 (SD 7) frames). Each stride was temporally registered to 101 data points.

4.2.3 Data Analysis

In Chapter 3, the ellipse area method was proposed as a method for calculating coordination variability that was robust to the vector length. In that method, vectors were defined between consecutive data points on an angle – angle plot. These vectors represented the dynamics of the coupling angle interactions (Figure 4.2A&B). Vectors that occurred at the same temporal percentage of the movement were then normalised to originate from the origin (Figure 4.2C) and an ellipse was formed around their end points (Figure 4.2D). The area of this ellipse provided a quantitative representation of vector coding variability.

Whilst vector coding is commonly described as originating from the angle – angle plot (e.g. Figure 4.2A), it is also possible to create a complementary visualisation for the vector coding method by creating a $\Delta\theta$ – $\Delta\theta$ plot (Figure 4.2E). Within biomechanical conventions it is standard to calculate the three-dimensional (3D) angular velocity to represent angular dynamics (Equation 4.3). In this vein, the $\Delta\theta$ – $\Delta\theta$ plot in Figure 4.2E could be considered an approximation of the angular velocity – angular velocity plot in Figure 4.2F.

In order to compare the two approaches quantitively, ellipse area coordination variability was calculated using the traditional $\Delta\theta$ input (Difference Ellipse Method – DEM) or with angular velocities as inputs (Velocity Ellipse Method – VEM). All possible combinations of the triplanar (X,Y,Z) hip knee and ankle joint angles (36 possible pairings) were computed and compared. The hip flexion/extension– knee flexion/extension coupling was singled out for particular focus as its results contained unusual features.

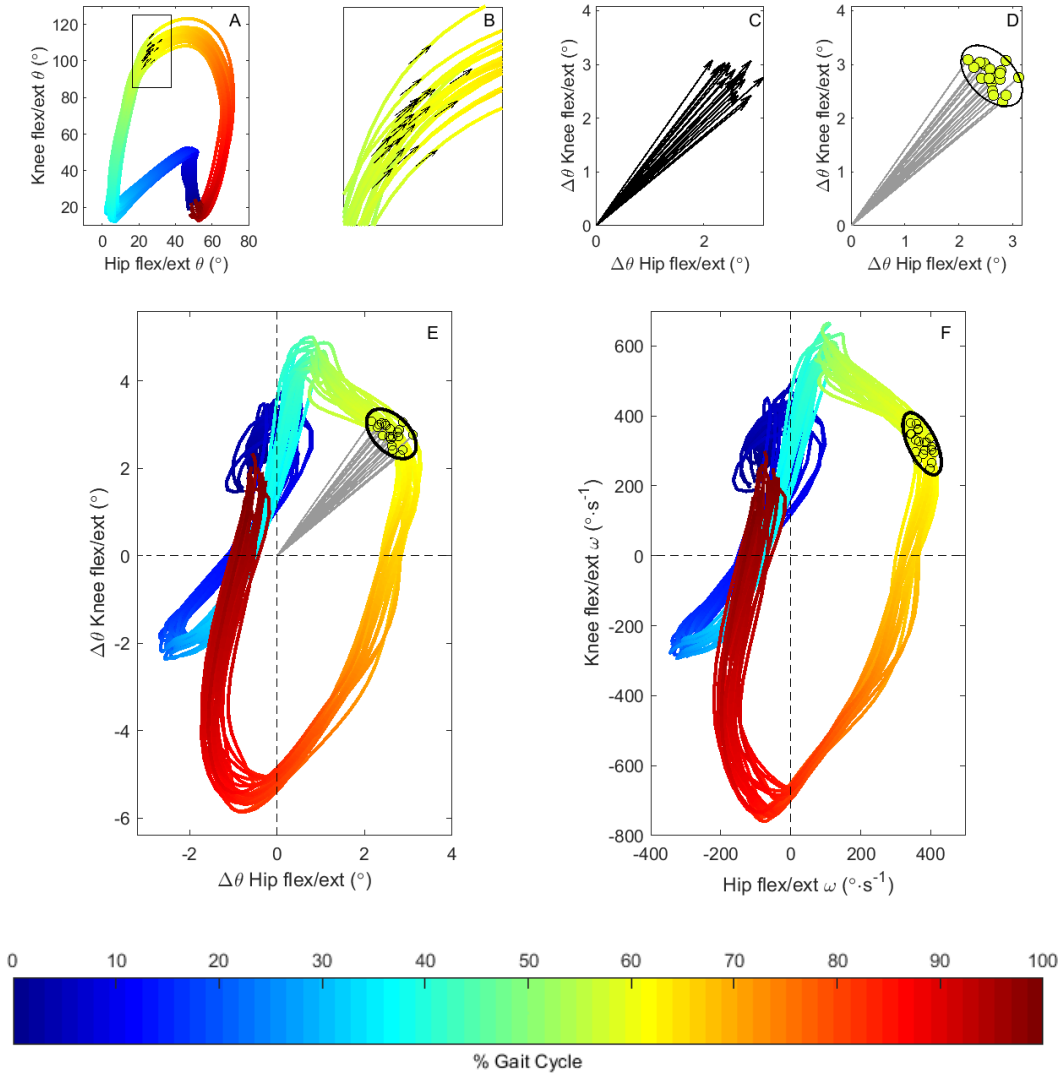


Figure 4.2. The association between traditional depictions of vector coding, the ellipse area method and how the velocity ellipse area is a comparable alternative. A) Hip flexion/extension – knee flexion/extension angle – angle plot of 20 gait cycles. B) Magnification of time points from 59 to 60% of the time normalised gait cycle with vectors between these time points highlighted in black. C) Vectors highlighted in B normalised to the same starting point. D) Creation of ellipse around the 20 end points of the normalised ellipses shown in C. E) The same data displayed in D is highlighted in this image, alongside data from the rest of the gait cycle as an alternative means of visualising joint coupling data and demonstrating the Difference Ellipse Method (DEM)). F follows the same principle as E but angular velocities have been plotted in place of $\Delta\theta$ so the plot demonstrates the Velocity Ellipse Method (VEM).

Covariance matrix calculation

The ellipse area calculation method used in this thesis first require the calculation of a covariance matrix from clusters of data points sampled at each temporally normalised time point. The covariance matrices were calculated using the same equations but with different inputs for the DEM compared to the VEM, so these calculation steps have been detailed separately.

Difference ellipse covariance matrix calculation

The difference in joint angle ($\Delta\theta$) between each temporally normalised percentage of the gait cycle (t) was calculated for all twenty gait cycles for both the joint angle displayed on the x axis of the angle – angle plot (θ_x) and the joint angle displayed on the y axis of the angle – angle plot (θ_y) using equations 3.5 and 3.6 respectively (Chapter 3, Section 3.2.4). From these, a covariance matrix (K_{DEM}) was calculated across the twenty gait cycles (c) at each time point (Equations 3.7 and 3.8).

Velocity ellipse covariance matrix calculation

The covariance matrix for the velocity ellipse method was formed from the angular velocities displayed on the x axis (ω_x) and the y axis (ω_y) of the angular velocity – angular velocity plot. In detail: the mean angular velocity ($\bar{\omega}$) was calculated across the twenty (C) gait cycles (c) at each time point for ω_x and ω_y:

$$\bar{\omega} = \frac{\sum_c^C \omega}{C} \tag{4.7}$$

The covariance matrix (K_{VEM}) was then calculated at each time point across c stride cycles:

$$K_{VEM} = \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{C} & \boldsymbol{D} \end{bmatrix} \tag{4.8}$$

$$\boldsymbol{A} = \frac{1}{(n-1)\sum_c^C \left(\omega_{x_c} - \overline{\omega_x}\right)^2}$$

$$\boldsymbol{B} = \boldsymbol{C} = \frac{1}{(n-1)\sum_c^C \left(\omega_{x_c} - \overline{\omega_x}\right)\left(\omega_{y_c} - \overline{\omega_y}\right)}$$

$$\boldsymbol{D} = \frac{1}{(n-1)\sum_c^C \left(\omega_{y_c} - \overline{\omega_y}\right)^2}$$

Ellipse area calculation

The remainder of the ellipse area calculations are common to both the DEM and VEM. In brief, eigenvalues were calculated (Equations 3.9 to 3.13) from the respective covariance matrices (K_{DEM} and K_{VEM}). A scaling factor, k, was calculated based on the probability, p = 0.95, that a future data point would lie within the defined ellipse from the inverse of the chi-squared cumulative distribution function for 2 degrees of freedom (Schubert and Kirchner,

2014; Mullineaux, 2017) using Equation 3.14. Ellipse axes were defined by calculating the root of each eigenvalue and scaling these by *k* (Equation 3.15). The product of the ellipse axes were then multiplied by π to give an ellipse area (Equation 3.16) for the DEM (V_{DEM}) and VEM (V_{VEM}) within which there is a 95% probability a future observation will fall. A greater ellipse area represented higher coordination variability.

Comparison of VEM and DEM

A normalised cross-correlation (Equation 4.9) was performed with the V_{DEM} and V_{VEM} signals for each participant and coupling to assess how similar the results of the VEM and DEM methods were. The normalised cross-correlation detects the correlation of two signals that have different power. Its values range from 1 to -1 where 1 indicates exact correlation, -1 indicates the signals are opposites and 0 represents no correlation at all. The normalised cross-correlation required both signals to have the same length. The DEM calculates coordination variability by finding the difference between consecutive data points. The DEM therefore has one less temporal node than the VEM when calculated from the same temporally normalised time series data. The DEM output can therefore be considered as most representative of the timepoint directly in the middle of the two points from which it was calculated (i.e. the first data point best represents 0.5% of the gait cycle). Thus, in order to perform the normalised cross correlation, the V_{VEM} signal was spline interpolated so that 100 data points were extracted, omitting the initial and final 0.5% of the cycle. A normalised cross correlation time series (C_p) was calculated by computing the correlation between signals V_{VEM} and V_{DEM} at each possible temporal overlap [τ] for each participant (p)

$$\mathrm{C}[\tau] = \frac{\sum_{-\infty}^{\infty} V_{VEM}[t] \cdot V_{DEM}[t+\tau]}{\sqrt{(\sum_{-\infty}^{\infty} V_{VEM}[t] \cdot V_{VEM}[t+\tau]) \cdot (\sum_{-\infty}^{\infty} V_{DEM}[t] \cdot V_{DEM}[t+\tau])}} \qquad (4.9)$$

The central value from the cross-correlation was extracted (C_{MID}) and the mean was calculated across the data from all *P*=20 participants for each coupling:

$$\overline{C_{MID}} = \frac{\sum_{p=1}^{P} C_{MID_p}}{P} \qquad (4.10)$$

4.3 Results

Across the 36 different joint angle couplings the average (across participants) correlation between V_{VEM} and V_{DEM} was lowest for the hip ab/adduction – knee ab/adduction coupling ($\overline{C_{MID}}$ = 0.923) and highest for the ankle inversion/eversion – ankle ab/adduction coupling ($\overline{C_{MID}}$ = 0.998) (Table 4.1).

Table 4.1. Average maximum cross correlation values ($\overline{C_{MID}}$) across participants for each coupling combination. All possible coupling combinations from the following joint angles are represented: Ankle (A), Knee (K) and Hip (H) in the sagittal (x), frontal (y), and transverse (z) joint rotational planes. The cross correlation shows the correlation between coordination variability calculated using the velocity ellipse method compared to the difference ellipse method. Shading has been used to represent which cross correlations are highest or lowest based on a colour spectrum from green (highest) to red (lowest).

	Ax	Ay	Az	Kx	Ky	Kz	Hx	Hy	Hz
Ax									
Ay	0.989								
Az	0.996	0.998							
Kx	0.996	0.992	0.994						
Ky	0.936	0.940	0.947	0.938					
Kz	0.976	0.976	0.971	0.975	0.995				
Hx	0.995	0.992	0.994	0.991	0.945	0.969			
Hy	0.969	0.963	0.964	0.969	0.920	0.942	0.969		
Hz	0.991	0.982	0.987	0.990	0.924	0.957	0.989	0.998	

Lowest — Highest

For individual participants the lowest (0.851) and highest (>0.999) normalised cross correlations were observed for the hip ab/adduction – knee ab/adduction in participant 5 and ankle inversion/eversion – ankle ab/adduction couplings in participant 20 respectively (Figure 4.3).

In observing the V_{DEM} time series for certain couplings, it was noticed that unusual features were present in those couplings which contained the knee flexion/extension angle therefore the hip flexion/extension – knee flexion/extension coupling has been presented in more detail to look into this feature in greater detail. Qualitatively, the V_{VEM} and V_{DEM} signals for hip flexion/extension – knee flexion/extension were visually similar in their pattern for all 20 participants. This can be seen in Figure 4.4 for two example individuals.

On visual inspection of the graphs, 17 of the 20 participant time series that were calculated using the DEM contained spikes in the hip flexion/extension – knee flexion/extension coupling that did not correspond with the smoothness of the rest of the time series (e.g. Figure 4.4A, grey trace at 60%, Figure 4.4B, grey trace at 76% of the gait cycle). A small amount of noise in just one cycle of the knee difference signal appeared at the same time as the spike in the V_{DEM} (Figure 4.5D). The magnitude of this noise was less than half a degree and therefore was undetectable to the eye when inspecting the angle trace from which it was calculated (Figure 4.5B) but could be observed in the $\Delta\theta$ traces and the standard deviation of the measure

at those time points (Figure 4.5D). The same noise did not appear in the angular velocity traces (Figure 4.5F). When the trial in which the noise was observed was removed from the ellipse area calculation, the resulting ellipse area was 27% smaller than when it was included (Figure 4.6).

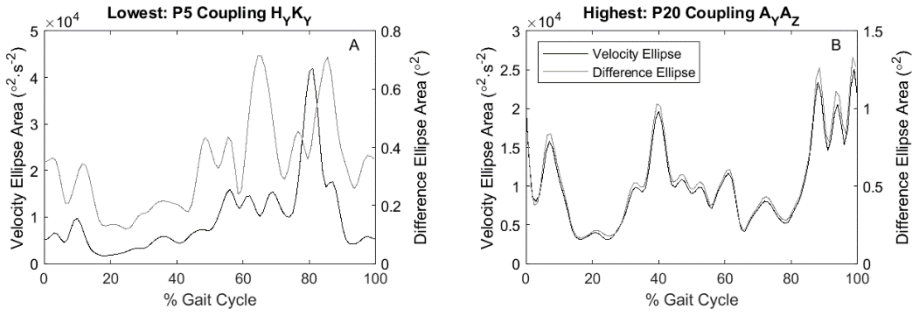


Figure 4.3. Velocity Ellipse Method (black line) and Difference Ellipse Method (grey line) coordination variability time series for the participant and coupling that had the A) lowest correlation and B) highest correlation (B). The lowest correlation observed was from participant 5 (P5) in hip ab/adduction – knee ab/adduction (H_YK_Y, normalised cross correlation of 0.851) and the highest was from participant 20 (P20) for ankle inversion/eversion - ankle ab/adduction (A_YA_Z, normalised cross correlation of >0.999).

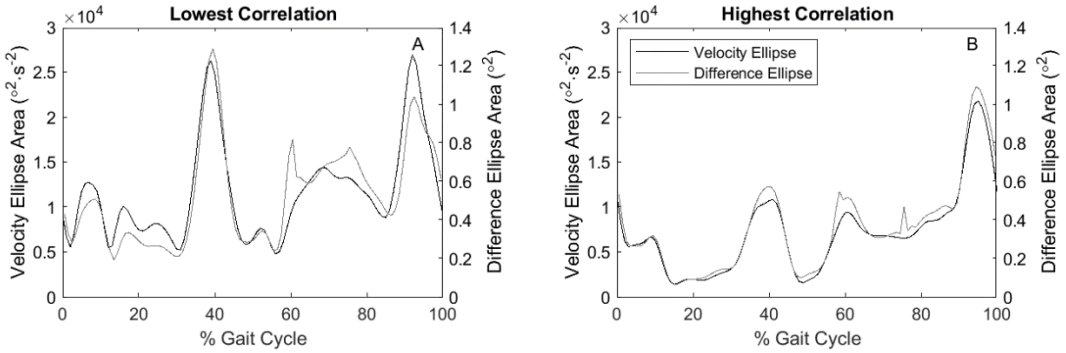


Figure 4.4. Comparison of coordination variability measured using the Difference Ellipse Method (grey) and Velocity Ellipse method (black). The participants with the A) lowest (participant 4 , C_{MID} = 0.984) and B) highest (participant 19, C_{MID} = 0.998) normalised cross correlations for the hip flexion/extension – knee flexion/extension between coordination variability measured using the difference and velocity ellipse methods are shown.

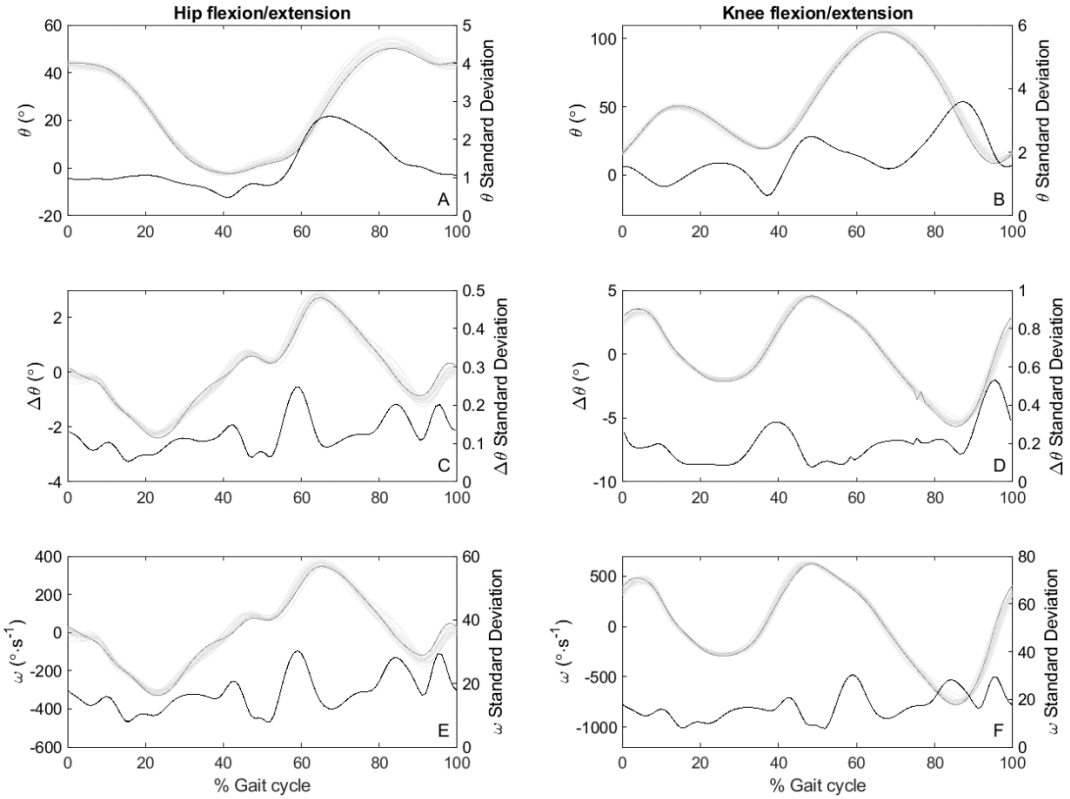


Figure 4.5. Detailed joint angle and joint angular velocity data relevant for the calculation of coordination variability displayed in Figure 4.4B. Joint angles (θ) and the univariate spread (standard deviation in black) at each time point for A) hip flexion – extension and B) knee flexion – extension. The difference between normalised time points ($\Delta\theta$) in C) hip flexion – extension and D) knee flexion – extension with the respective standard deviations (black). Joint angular velocities (ω) for D) hip flexion – extension and E) knee flexion - extension with the respective standard deviations (black). All data is from one participant (P19) and shows 20 gait cycles. Cycle 7 is highlighted in a darker grey to emphasise a knee flexion – extension $\Delta\theta$ trace (plot D at 76% of the gait cycle) that does not match the smoothness of the rest of the curve. The same feature is not apparent in the knee angle (B) or the knee angular velocity (F)

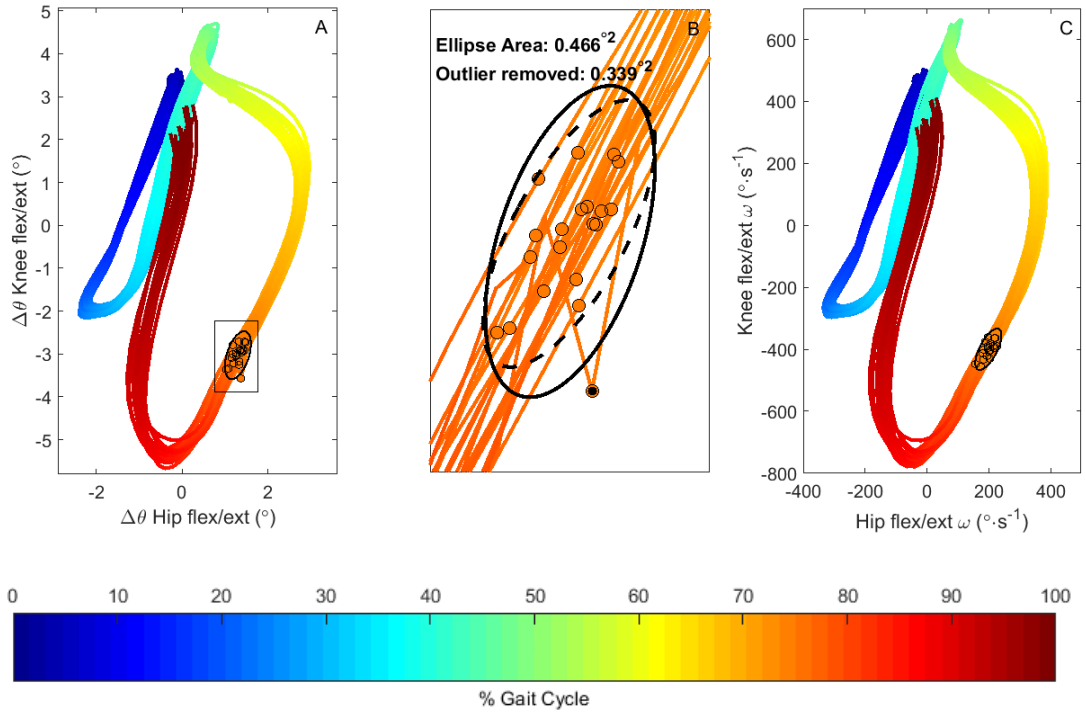


Figure 4.6. Detailed bivariate plots demonstrating why a spike in variability was observed in the difference ellipse method coordination variability but not the velocity ellipse method in Figure 4.4B. A) $\Delta\theta - \Delta\theta$ plot for one participant (P19) B) Magnified area of A demonstrating the effect of including all data points in the ellipse area calculation (solid line ellipse), compared to removing the outlier (dashed ellipse). The manually identified outlier data point is highlighted with a black centre. C) Angular velocity – angular velocity plot for the same participant's data with no evidence of an outlier at the corresponding time point.

4.4 Discussion

The aim of this chapter was to investigate and discuss the potential benefits and shortcomings of using traditional inputs for calculating ellipse area coordination variability (the Difference Ellipse Method – DEM) compared to the use of 3D angular velocities (the Velocity Ellipse Method – VEM). The two different approaches were applied to the same data sets and the coordination variability measured from each method was compared using a normalised cross correlation. The cross correlations were generally high suggesting similarity in the relative changes that were observed in coordination variability regardless of whether the traditional $\Delta\theta$ or angular velocity inputs were used. The level of similarity varied according to the coupling used, so some data is not as accurately represented using the $\Delta\theta$ approximation as others. Coordination variability measured using 3D angular velocity inputs was also found to be more robust to noise in the joint angle signal that was observed in couplings that comprised knee joint flexion/extension angles compared to the traditional approach.

The correlations between the DEM and VEM were all greater than 0.851. This is suggestive of generally good correspondence between the two measures although it is challenging to identify a cut off correlation value whereby the DEM would no longer be considered a good

representation of the VEM. Qualitatively in Figure 4.3A the DEM does not provide a good representation of the VEM, yet the quantitative correlation is still high (0.851) in relation to the possible range of values (-1 to 1). Biomechanical conventions state that the correct representation of angular dynamics is via 3D angular velocities therefore it seems prudent that any research with 3D data available would be best placed to use angular velocities. The differences observed between DEM and VEM time series shapes are caused by the differences in how angular dynamics are calculated (e.g. in Figure 4.5C and E subtle differences in the shape can be observed around 50% of the gait cycle where a greater decrease is observed in $\Delta\theta_{H_{FE}}$ than in $\omega_{H_{FE}}$). This and other differences between the VEM and DEM can either be the result of: contributions from other angular movements that are accounted for in 3D angular velocities (Equation 4.3), differences in the temporal information that is retained (i.e. in DEM only within cycle temporal information or in VEM both within and between cycle temporal information) or a combination of both factors. These differences appeared to have lesser or greater effects according to which coupling was analysed (Table 4.1, Figure 4.3). The results presented are however specific to the data collected. If a project was only able to collect 2D data, it is important that similar preliminary tests are conducted, as have been demonstrated here. The preliminary tests must be specific to the movement of interest to understand which coordination variability values are best replicated by them DEM as different joint ranges of motion, rates of change in angle, and the similarity in length of repeated trials will all affect how well the $\Delta\theta$ input represents the angular velocities. Given a lack of reference values for what correlation value is high enough to show good representation it would be important to combine quantitative and qualitative assessments in the decision-making process.

The temporal differences between the DEM and VEM were not tested experimentally but the theoretical differences between them were presented in the introduction in an exaggerated simulated scenario (Figure 4.1). As an additional note, the differences between the DEM and VEM that are caused by temporal differences should be minimal where repeated cycles of the movement are all very similar lengths. Because the DEM does not account for between cycle temporal differences, if there are no differences in the lengths of each movement cycle, the absence of between cycle temporal information in the DEM will have no effect and temporal distortion between cycles will be minimal. The greater the differences in the lengths of the movement cycles, the greater the contribution temporal factors will have in explaining differences between the DEM and VEM. The VEM automatically accounts for temporal differences between movement cycles, therefore has an advantage over the DEM in this respect where temporal information has been suggested as valuable (van Emmerik, Miller and Hamill, 2014)

An additional aspect that was highlighted by comparing the DEM and VEM was that the velocity method appeared to be less sensitive to noise than the difference method (e.g. Figure 4.4B at 67%). To understand why the noise was present in the difference signal but not in the angular velocity, the example that is shown in Figure 4.4B was explored in greater detail by inspecting the data which was used for the calculation. The noise can be isolated to having been caused by a spike in one cycle of the knee difference signal (Figure 4.5D). The magnitude of this spike is less than half a degree and therefore is undetectable to the eye when inspecting the angle trace from which it was calculated (dashed black line, Figure 4.5B). The same noise cannot be seen in the angular velocity signal (Figure 4.5F). Possible causes could be: an error in the DEM data as a result of not considering movement in other planes of motion, additional smoothing inherent to the central finite difference method or a combination of both. Further work would be required to quantitatively identify the source of the noise and exactly why it is not shown in the angular velocity data.

Another interesting observation from the same feature was the extent to which an outlier can impact the covariance matrix calculations used to form the ellipse about the multiple time points. Whilst the source of the outlier in the example was not present when the angular velocity input was used, it served as a valuable reminder that the ellipse area calculation can be sensitive to outliers. In examples where the outlier is believed to be the result of possible errors in measurement or methods there is just reason to extract a trial (Hodge and Austin, 2004; Mullineaux and Irwin, 2017). Aside from this, the existence of outliers presents a thought-provoking challenge for researchers in general (Hodge and Austin, 2004) but particularly so for those interested in measuring coordination variability. The relationship between single, or possibly multiple outliers and ellipse area is not simple and is affected by the distribution of the other data points across which the ellipse area is calculated. It must be considered that the presence of outliers could negatively impact the repeatability of the coordination variability measure, particularly when the number of movement repetitions across which variability is calculated is low whereby outliers comprise a higher percentage of the total sample. Conversely, the removal of outliers would directly impact and bias the variability measure. In this thesis, outliers will not be removed to avoid the risk of potential bias caused by their extraction. The observations from this chapter however highlight the importance of measuring the repeatability of variability. A better understanding of the potential sensitivity and its effect on repeatability of the measure will help guide informed decisions for use of coordination variability measures and whether further methodological considerations are necessary to make coordination variability measures more effective.

Finally, the focus of this thesis is specifically on the measurement of coordination variability, but many of those who are interested in coordination variability are also interested in

coordination (e.g. Floría et al., 2019; Weir et al., 2019). Some comment is therefore also beneficial on how this alternative approach of using angular velocities may fulfil both requirements. The vector coding method first demonstrated by (Heiderscheit, Hamill and van Emmerik, 2002) has previously been highlighted as a simple depiction of coordination that is easy to understand for practitioners or clinicians without training in biomechanics, particularly when compared to the alternative continuous relative phase method (van Emmerik, Miller and Hamill, 2014). The commonly known starting point of vector coding is the angle – angle plot and the coordination measure derived from this is the coupling angle (the angle that each vector connection consecutive data points on the angle-angle plot makes with the x-axis). The angle – angle plot provides information about the angular positions during the movement, but the coupling angle coordination measure can be more challenging to extract from this plot at first glance, as the reader must first understand the chronological sequence of the data and then consider the direction of travel in relation to the horizontal . Consequently, coordination if often depicted as a coupling angle against time (Ferber, Davis and Williams, 2005; Dierks and Davis, 2007; Chang, van Emmerik and Hamill, 2008; Needham, Naemi and Chockalingam, 2015; Celestino et al., 2019; Davis et al., 2019) or is binned into different movement phases which indicate segment / joint dominancy and/or in phase or anti phase movement (Chang, van Emmerik and Hamill, 2008; Armour Smith, Popovich and Kulig, 2014; Needham, Naemi and Chockalingam, 2015; Hafer et al., 2016; Celestino et al., 2019; Floría et al., 2019; Harrison et al., 2019; Beitter, Kwon and Tulchin-Francis, 2020). Researchers and practitioners wishing to utilise angular velocities in their coordination work in place of the traditionally used $\Delta\theta$ to maintain a level of consistency between coordination and coordination variability methods would be able to calculate the coupling angle (γ) at any given time point using angular velocities using the following equation:

$$\gamma = \tan^{-1}\left(\frac{\omega_y}{\omega_x}\right) \tag{4.11}$$

where ω_x is the angular velocity of the first joint or segment angle in the coordination pairing plotted on the x-axis and ω_y is the angular velocity of the second joint or segment angle in the coordination pairing plotted on the y-axis. The resulting coupling angles can be interpreted in the same way as has traditionally been done. Furthermore, the angular velocity – angular velocity plot provides an alternative option for visualising which coordination pattern is prevalent at each percentage of the movement (e.g. Figure 4.7). Thus coordination measures can still be applied in a very similar fashion to those that have been presented using the Heiderscheit vector coding method and the representation of the angular velocity – angular velocity plot adds another dimension to the visualisation of the coupling angle.

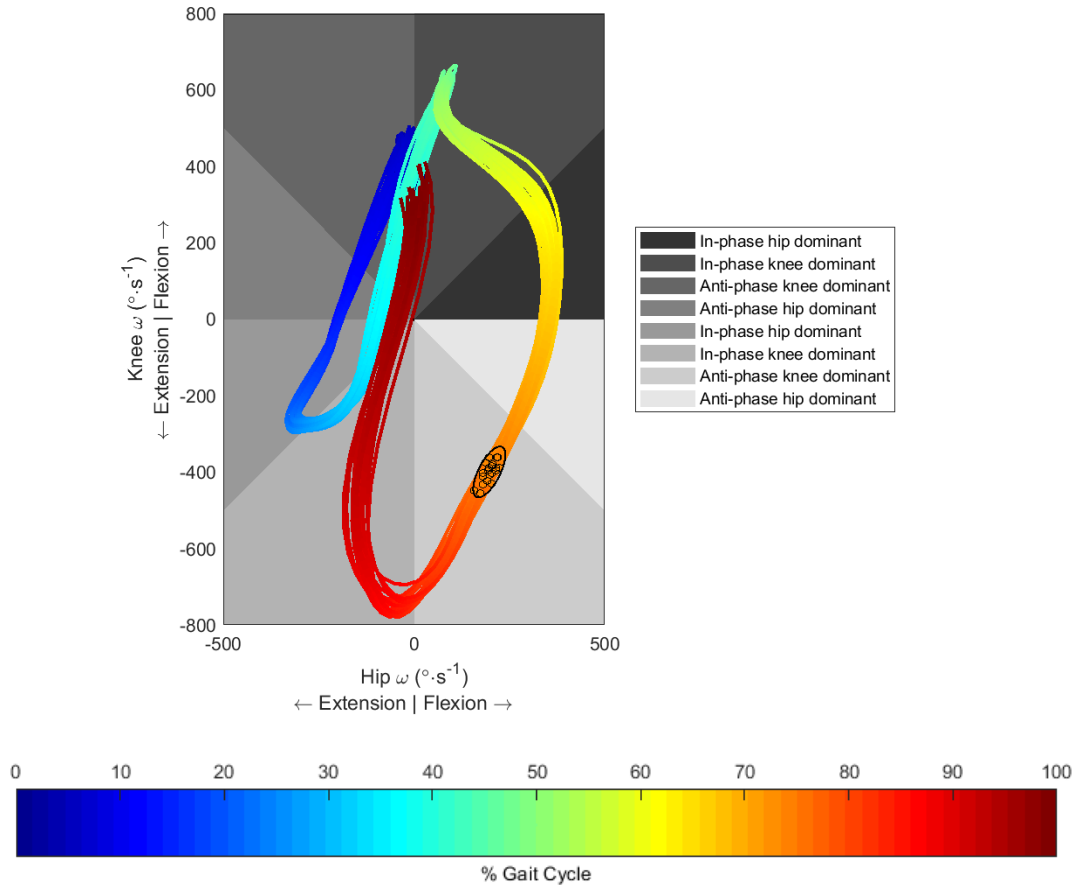


Figure 4.7. Example depiction of angular velocity – angular velocity plot (for hip flexion/extension and knee flexion/extension velocity) and how it can offer an alternative method to display coordination data. The eight coordination bins proposed by Needham, Naemi and Chockalingam (2015) are indicated by each of the greyscale shaded areas. At any percentage of the movement (represented by colour) the coordination pattern in use can be identified according to the area of the graph it is in. For example, the highlighted ellipse at 76% of the gait cycle demonstrates an anti-phase knee dominant coordination pattern across all 20 gait cycle repetitions. It is also clear that the hip joint is flexing whilst the knee joint is extending because the ellipse is situated in the lower right quadrant.

4.5 Conclusion

This chapter investigated the advantages and disadvantages of using joint angle inputs to vector coding coordination variability methods in comparison to angular velocities for the ellipse area coordination variability method proposed in Chapter 3. The different features that result from choosing angle (the difference ellipse method) or angular velocity (the velocity ellipse method) inputs have been discussed within this chapter and a summary is provided in Table 4.2. The findings have informed the decision to proceed within the remainder of this thesis in using angular velocities as inputs to the coordination variability calculations. This was the best option for the thesis due to the availability of 3D data: by using the 3D angular velocities as inputs, the methods in this work will conform with biomechanical conventions for calculating angular dynamics, preserve more temporal information in the coordination

variability measure and results suggest it also make the measure more robust to any noise that may be present in the data.

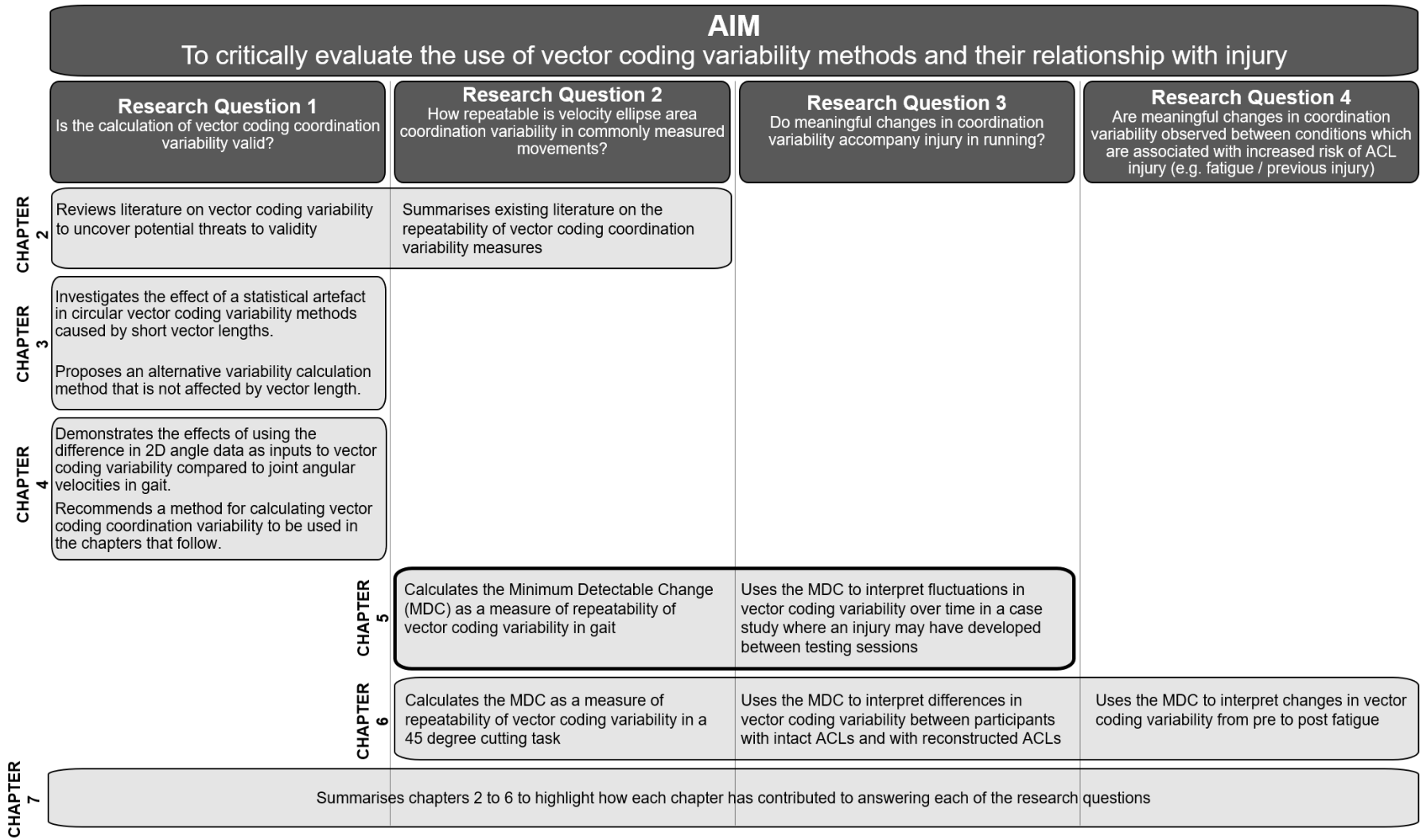
In situations where 3D angular velocities are not available, the results presented in this chapter indicated that calculating the difference between time points can provide comparable results to those attained from 3D angular velocities. However, the level of agreement differed between couplings and individuals. It is important to stress that the relationship will change depending on the joint angles, rates of change in joint angle and the consistency of trial length so the correlations presented in this research are not transferable to data collected at different gait speeds or from different movements. Researchers/users should investigate the appropriateness of the 2D simplification specific to their own needs.

Table 4.2. Comparison of the different features of using the difference in joint angles between data points compared to the 3D angular velocities for calculating ellipse area coordination and coordination variability.

	Difference Method (DEM)	**Velocity Method (VEM)**
Temporal information	Temporal information within the movement cycle is retained but between cycle temporal information is lost	Within and between movement cycle temporal information is retained
Available equipment	Possible with both 2D and 3D measurements	Only possible with 3D measurements
Accuracy	Does not use biomechanical conventions for representing angular dynamics. The 2D simplification can result in coordination variability measures that are very similar to the 3D dynamics but this is not guaranteed.	Uses biomechanical conventions to accurately represent angular dynamics.
Noise	Sensitive to noise in the angle data.	More robust to noise in the angle data
Compatibility with coordination measures	The difference in angles can be used to calculate both coordination and coordination variability.	The 3D angular velocities can be used to calculate both coordination and coordination variability.

Finally, the presence of noise in the difference ellipse method highlighted the effect that outliers of any kind can have on ellipse area calculations. This emphasised the importance of understanding the repeatability of the coordination variability measured using the ellipse area

method: a topic that will be addressed in the following two chapters in two different movements which have been investigated in coordination variability – injury research.


AIM
To critically evaluate the use of vector coding variability methods and their relationship with injury
Research Question 1
Is the calculation of vector coding coordination variability valid?
Research Question 2
How repeatable is velocity ellipse area coordination variability in commonly measured movements?
Research Question 3
Do meaningful changes in coordination variability accompany injury in running?
Research Question 4
Are meaningful changes in coordination variability observed between conditions which are associated with increased risk of ACL injury (e.g. fatigue / previous injury)
CHAPTER 2
Reviews literature on vector coding variability to uncover potential threats to validity
Summarises existing literature on the repeatability of vector coding coordination variability measures
CHAPTER 3
Investigates the effect of a statistical artefact in circular vector coding variability methods caused by short vector lengths.
Proposes an alternative variability calculation method that is not affected by vector length.
CHAPTER 4
Demonstrates the effects of using the difference in 2D angle data as inputs to vector coding variability compared to joint angular velocities in gait.
Recommends a method for calculating vector coding coordination variability to be used in the chapters that follow.
CHAPTER 5
Calculates the Minimum Detectable Change (MDC) as a measure of repeatability of vector coding variability in gait
Uses the MDC to interpret fluctuations in vector coding variability over time in a case study where an injury may have developed between testing sessions
CHAPTER 6
Calculates the MDC as a measure of repeatability of vector coding variability in a 45 degree cutting task
Uses the MDC to interpret differences in vector coding variability between participants with intact ACLs and with reconstructed ACLs
Uses the MDC to interpret changes in vector coding variability from pre to post fatigue
CHAPTER 7
Summarises chapters 2 to 6 to highlight how each chapter has contributed to answering each of the research questions

CHAPTER 5: REPEATABILITY AND A LONGITUDINAL CASE STUDY OF COORDINATION VARIABILITY IN RUNNING GAIT

5.1 Introduction

Repeatability measures (also known as absolute reliability measures) indicate the degree of agreement between measurements taken under identical conditions within a short enough period of time where one would not expect change (Taylor and Kuyatt, 1994). Repeatability is an important characteristic to be aware of when collecting any data. It determines how much variation can be expected and can therefore help researchers decide if the difference between two groups of people or a difference within the same person over time represents a real difference (Hopkins, 2000). If the difference observed is lower in magnitude than the repeatability of the signal, the researcher can conclude that the result is more likely caused by fluctuations in the measurement (Hopkins, 2000).

Fluctuations in a measurement can be caused by a number of different factors. Whilst good research designs can minimise errors that may increase the variability of the main outcome measure (Mullineaux, Bartlett and Bennett, 2001) it is not possible to totally eliminate the sources of variation in all circumstances, especially when research is conducted on living beings. Variation can originate from different sources: the measurement tools, intra- and inter-operator differences in the use of measurement tools, biological variation in the participant's ability to repeat a task, and the environment (Preatoni et al., 2013). Thus, it is important to understand the different sources of variation that might be present in a particular dataset and their probable magnitudes. Differences between two measurements (between group or within individual) that exceed the magnitude of expected variation are interpreted as meaningful changes, while those below the threshold are not considered important.

To date, there has been very little research concerning the repeatability of coordination variability from angle – angle plots in running gait. In 2012, a doctoral thesis (Cunningham, 2012) investigated how repeatable a variety of coordination variability measures were when calculated from a different selection of strides (even vs odd gait cycles from a set of 10 consecutive strides). Coordination variability was measured in six knee – ankle joint couplings over eight different time intervals within the gait cycle. The confidence intervals that represented the range of values within which 95% of differences in coordination variability could be expected to fall when using the even compared to the odd gait cycles ranged from ± 1.3° to 14.9°. A 95% confidence interval of ±14.9° is approximately ±18% of the possible

magnitude of the variability signal for the measure that was used (Heiderscheit, Hamill and van Emmerik (2002), maximum value ~81°).

More recently, Hafer and Boyer (2017) investigated how many gait cycles were necessary to use in the calculation of coordination variability for the measure to stabilise (in the paper, defined as reaching within 10% of the value calculated from 15 strides) in treadmill running. They investigated four coordination couplings that combined pelvis thigh, shank and rearfoot segment angles and averaged coordination variability across: the whole of stance, terminal swing, early stance, mid stance and late stance. The authors concluded that a minimum of 8 gait cycles should be used in running. However, the authors also highlighted that the number of trials required varied according to participant. For example, although on average the group were within 10% of the value calculated from 15 strides at 8 strides, two of the ten participants recorded coordination variability values approximately 20% less than their 15 stride value for the thigh sagittal – shank sagittal coupling.

Finally, Smith and Kulig 2016 retested a subset of participants (four) as part of a larger cross-sectional study design in order to estimate absolute reliability of trunk – pelvis coordination variability of the stance phase of turning gait. Results indicated high absolute reliability with a standard error of measurement of 0.23°.

The method for calculating coordination variability used in the reliability research conducted to date was first used by Heiderscheit, Hamill and van Emmerik (2002). Chapter 3 showed that the Heiderscheit method is affected by a statistical artefact and therefore a new velocity ellipse method (VEM) was proposed across chapters 3 and 4. Overall, in the published literature, there have been some positive repeatability metrics for the Heiderscheit method but also some areas that required further insight. The variables (i.e. couplings of angular displacement) that are used to calculate coordination variability in the Heiderscheit method are related to those in the VEM (i.e. couplings of angular velocity) therefore any threats to repeatability observed for one method may also be relevant for the other. In Chapter 4 it was additionally highlighted that the VEM may be sensitive to outliers. Thus, understanding the repeatability of the VEM in common data collection settings is important for the future use and interpretation of the VEM and other related coordination variability measures.

Furthermore, a number of authors have highlighted the need for longitudinal datasets in coordination variability – injury research to better understand whether variability plays a causative role in injury, and how coordination variability may then change as the injury progresses and heals (Desai and Gruber, 2020). Longitudinal datasets are challenging to collect as participants must be committed to volunteering their time on multiple occasions over long periods. For researchers investigating injury, there is also no guarantee that an injury

will be observed in the population studied. Thus, longitudinal data on coordination variability combined with an improved awareness of the repeatability of coordination variability measures are important steps forward to a better understanding of the possible links between coordination variability and injury.

Two separate foci are therefore identified within this chapter; the first is related to the repeatability (i.e. absolute reliability) of coordination variability in running gait, a theme about which no research has been published to date. The aim of this strand is to report the within and between day repeatability of coordination variability measures in running gait. Such information has the potential to provide the first steps to understanding what magnitudes of change might represent meaningful changes in coordination variability within an individual. It was hypothesised that within day coordination variability measures would be more repeatable than between day measures as greater biological variation might be expected to occur as more time elapsed between sessions.

The second focus of this chapter was to conduct a case study of an individual who developed heel pain between testing sessions. The first aim of the case study investigation was to understand whether coordination variability was low or high compared to the rest of the population. It was hypothesised that coordination variability would be low in this individual compared to the rest of the group in the first three sessions in line with the theory that low coordination variability might cause tissue damage due to repetitive loading. The second aim of the case study was to understand whether any meaningful changes in coordination variability had occurred within that participant between the different testing sessions that they attended. In this respect it was hypothesised that coordination variability would be higher in the final data collection session compared to the first three. This was hypothesised as the majority of research comparing injured and healthy populations has found coordination variability to be higher in the injured group (Baida et al., 2018) or the group that went on to report injuries (Desai and Gruber, 2020).

5.2 Methods

5.2.1 Study Design

In this chapter a repeated measures design was employed where the same data collection protocol was conducted four times (Figure 5.1). The 3-6 hour gap was chosen to allow a full recovery between data collection sessions. The period of a week was chosen because other researchers have suggested that 7 days is a short enough period to avoid real changes in a participant's gait (McDermott et al., 2010). The 8 week gap was considered a long enough time period that changes in injury status might be reported by some of the participants as

physiological adaptations have been observed over similar time scales in response to training interventions (Griffin and Cafarelli, 2005) .

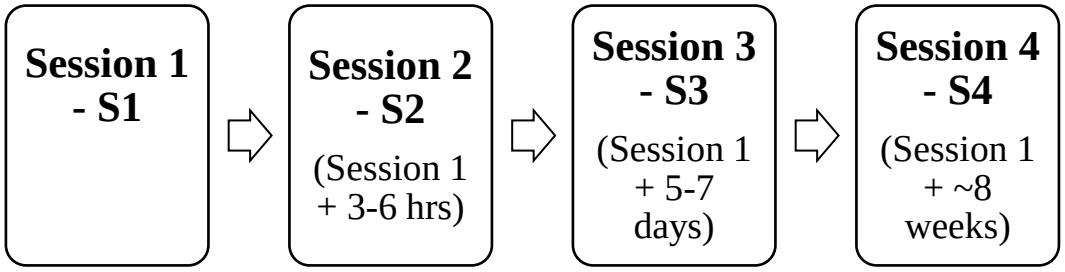


Figure 5.1. Overview of the four data collection sessions and the temporal separation between them.

5.2.2 Participants

Twenty athletes (10 male [height: 1.80 ± 0.06, weight: 71 ± 6 kg, age: 22 ± 3], 10 female [height: 1.68 ± 0.07 m, weight: 59 ± 10 kg, age: 20 ± 4 yrs]) who participated in running events of 5 km or greater were recruited from the University of Bath triathlon and athletics clubs to attend four data collection sessions in the University's Applied Biomechanics Lab. Inclusion criteria required these participants to be between 18 and 35 yrs old, free from neurological conditions, not currently suffering from injury and not to have missed training within the previous month due to injury. All participants provided informed consent to participate and the study was approved by the University of Bath Research Ethics Approval Committee for Health.

5.2.3 Data Collection

Before each data collection session began, participants were asked to report if they currently felt pain in their back and lower limbs and rated each pain score on a Likert scale of 1 (no pain) to 5 (extremely painful). Data pertaining to previous injuries (defined as something that disrupted their training for four weeks or longer) and self-reported recent 5 km running time were also collected.

A lower limb markerset was then applied to participants (Table 5.1, Figure 5.2). Markers were positioned in accordance with van Sint Jan (2007) marker guidelines.

Rigid plastic clusters with four markers apiece were attached with double sided tape to the participants' thighs and shanks and served as tracking markers for those segments. The

clusters were then also secured using self-securing bandages (Superwrap, Fabrifoam, Pennsylvania, USA) (Figure 5.2).

Table 5.1. Details of anatomical positions of the lower limb markerset.

Marker location	Abbreviation	Marker type
Anterior superior iliac spine	IAS	Anatomical + Tracking (Pelvis)
Posterior superior iliac spine	IPS	Anatomical + Tracking (Pelvis)
Greater trochanter	GT	Anatomical
Lateral femoral epicondyle	LFE	Anatomical
Medial femoral epicondyle	MFE	Anatomical
Lateral fibula malleolus	FAM	Anatomical
Medial tibia malleolus	TAM	Anatomical
5th Metatarsalphalangeal joint	5FM	Anatomical
1st Metatarsalphalangeal joint	1FM	Anatomical
Calcaneus *	HL	Anatomical + Tracking (Foot)
Foot 1 *	FT1	Tracking (Foot)
Foot 2 *	FT2	Tracking (Foot)

*** Participants were shod for testing and therefore these markers were placed on the shoe (Figure 5.2)**

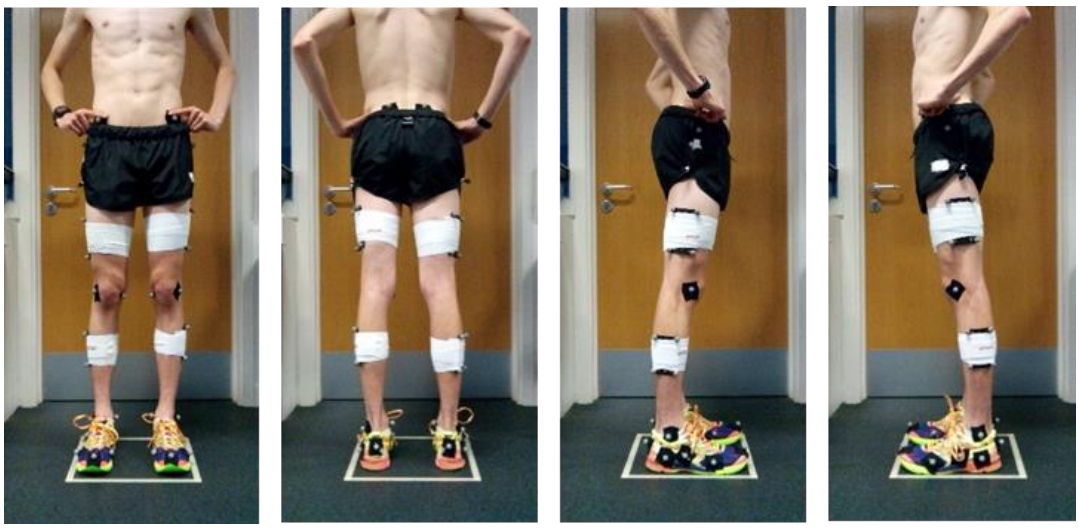


Figure 5.2. Markerset used for data capture.

In the first data collection sessions, photos were taken of each participant standing with standardised foot positioning, whereby the feet aligned with the inside lateral edges of the square markings on the floor of the lab (Figure 5.3). Images were taken from front, rear and both side views. In each subsequent data collection session a camera overlay app (Overlay, Add Quick) was used to conduct a visual check for each of the four views and minimise the likelihood of marker misplacement (e.g. note that Figure 5.3 (right) is the front view overlay image from one participant from session 1 and session 2 (Figure 5.3, left and middle)).

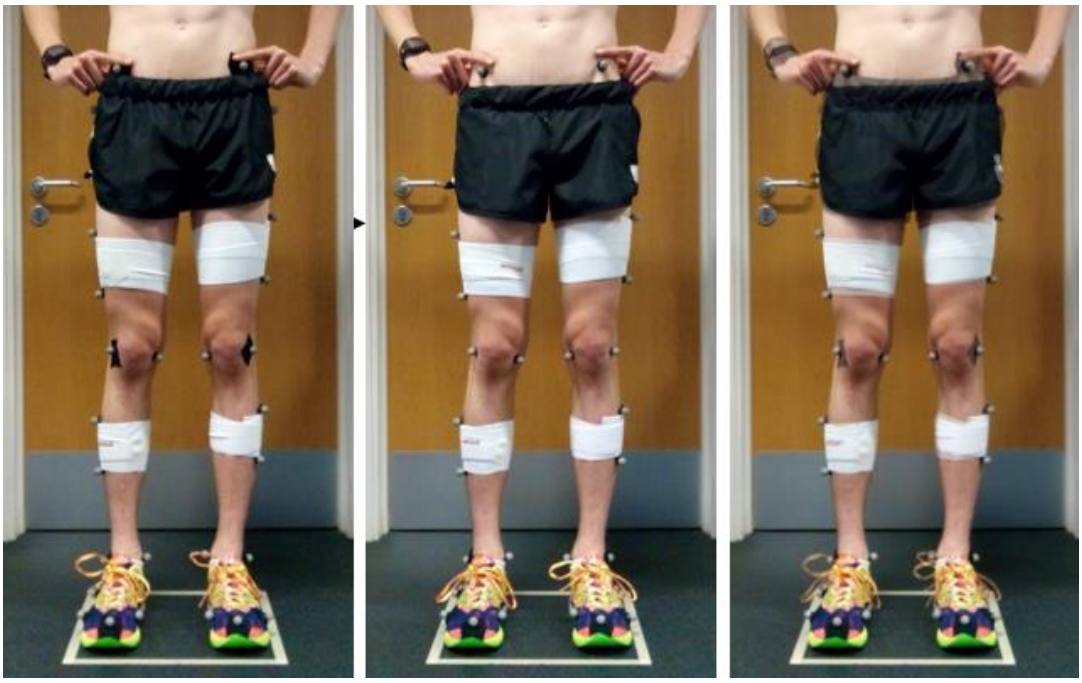


Figure 5.3. Example of overlay camera images for checking marker misplacement. (Left) Front camera image from session 1 (Middle) Front camera image from session 2 (Right) Images from session 1 and session 2 overlaid on one another.

A static recording was taken of the full markerset by the motion capture system (Qualisys AB, Sweden) prior to the removal of the medial markers (1FM, TAM, FME). Medial markers were removed to avoid obstruction of natural gait. All motion capture data was sampled at 200 Hz using a 15 camera system (13 Oqus 400, 1 Oqus 300 and 1 Oqus 201c cameras) set up as shown in Figure 5.4 and Figure 5.5.

Participants conducted a 5 minute incremental warm up on the treadmill (Powerjog J200, Expert Fitness UK ltd, South Wales). The treadmill had been modified to shorten the support arms situated either side of the belt so that they were less likely to obstruct the camera views of the markers. Participants started their warm-up at 8 km/h and increased by 1 km/h each minute. During this time the motion capture system was checked to ensure all markers could

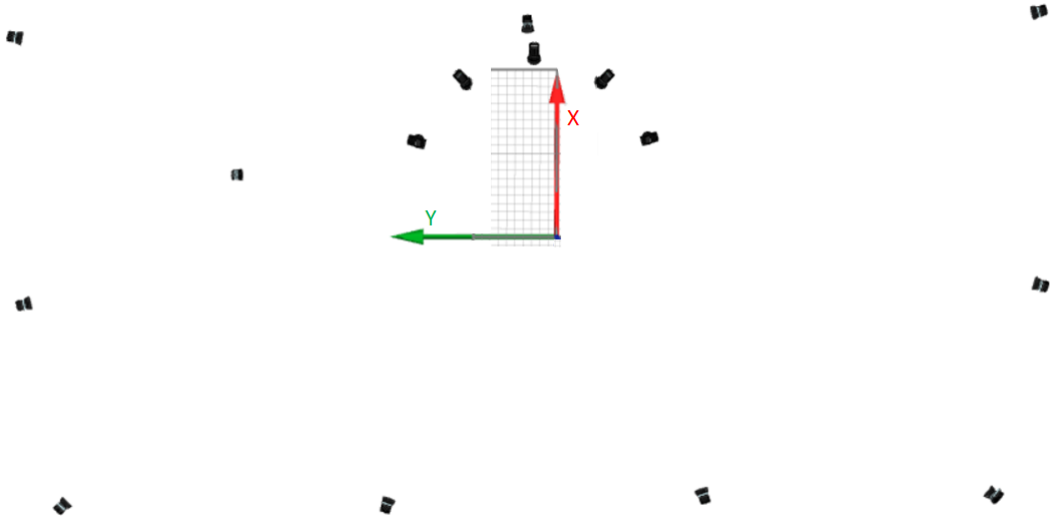


Figure 5.4. Aerial view of lab set up. Gridded area indicates approximate positioning of the treadmill belt.

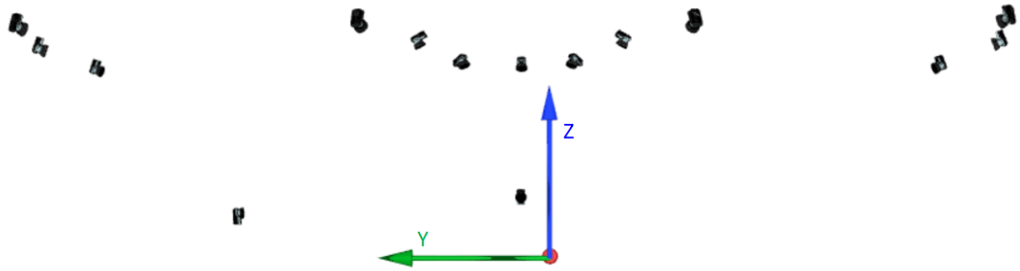


Figure 5.5. View of lab set up from the perspective of behind the treadmill.

be seen and tracked by the cameras. After the warm-up participants came off the treadmill for markers and clusters to be checked to ensure they were still firmly in place. Participants then completed 5 minutes' running at 12 km/h on the treadmill. The final minute of the 5 minutes was recorded using the motion capture system.

5.2.4 Data Processing

A total of twelve variables were calculated and analysed within this chapter, including four average coordination variability metrics, four time series of coordination variability and four time series of mean joint angle data (Table 5.2). A flowchart of analysis for the calculation of the three subsets of variables (coordination variability averaged over the gait cycle ($\bar{V}$), coordination variability time series (V) and mean joint angle time series ($\bar{J}$)) and their application is presented in Figure 5.6. The primary variables of interest were those of coordination variability for both the repeatability and case study components of this chapter.

Joint angle measurements were also analysed to understand how the repeatability of measurements taken as part of this chapter compared to those in other laboratories.

Table 5.2. Overview of dependent variables in Chapter 5. The variables are divided into three subsets: coordination variability averaged across the duration of the gait cycle ($\bar{V}$), coordination variability time series (V) and mean joint angle time series ($\bar{J}$).

Subset	Variables
$\bar{V}$ **(4 discrete variables)**	(1) Thigh flexion/extension – Shank flexion/extension (T_{FE}-S_{FE}) (2) Shank int/external rotation – Foot inversion/eversion (S_{EIR}-F_{IE}) (3) Hip flexion/extension – Knee flexion/extension (H_{FE}-K_{FE}) (4) Knee flexion/extension – Ankle inversion/eversion (K_{FE}-A_{IE})
V **(4 time-series variables)**	(1) Thigh flexion/extension – shank flexion/extension (T_{FE}-S_{FE}) (2) Shank internal/external rotation – foot eversion/inversion (S_{IER}-F_{IE}) (3) Hip flexion/extension – knee flexion/extension (H_{FE}-K_{FE}) (4) Knee flexion/extension – ankle eversion/inversion (K_{FE}-A_{IE})
$\bar{J}$ **(4 time-series variables)**	(1) Ankle Dorsi/Plantar flexion (A_{DP}) (2) Ankle Eversion/Inversion (A_{IE}) (3) Knee Flexion Extension (K_{FE}) (4) Hip Flexion/Extension (H_{FE})

All data were recorded and an automatic marker identification model (AIM model, Qualisys) was used to identify the markers in Qualisys Track Manager (Qualisys AB, Sweden). The marker trajectory data were exported to Visual 3D (v.6, C-Motion Inc, Germantown, MD, USA) where they were filtered using a low-pass, second order recursive Butterworth filter with a cut-off of 8 Hz. This cut-off frequency was selected using residual analysis (Winter, 2009). Lower limb segments were defined in Visual 3D as stated in Table 5.3. Segment angular velocities, joint angles and joint angular velocities were calculated in the Visual3D pipeline for the three rotations of the pelvis, thigh, shank and foot segments and the hip knee and ankle joints. All joints resolved the distal segment in the coordinate system of the proximal segment using an X-Y-Z Cardan sequence. For the left leg ab/adduction and rotation joint angles and velocities were negated so that positive numbers indicated the same anatomical motion in the left leg data as in the right.

Segment and joint angles and angular velocities were exported to MATLAB (2018B, The Mathworks Inc., Natick, USA). Raw trajectories of the heel, fifth metatarsal and toe markers were also exported to MATLAB and filtered using a low-pass, second order recursive Butterworth filter with a cut-off of 15 Hz, to be used in a validated foot contact algorithm

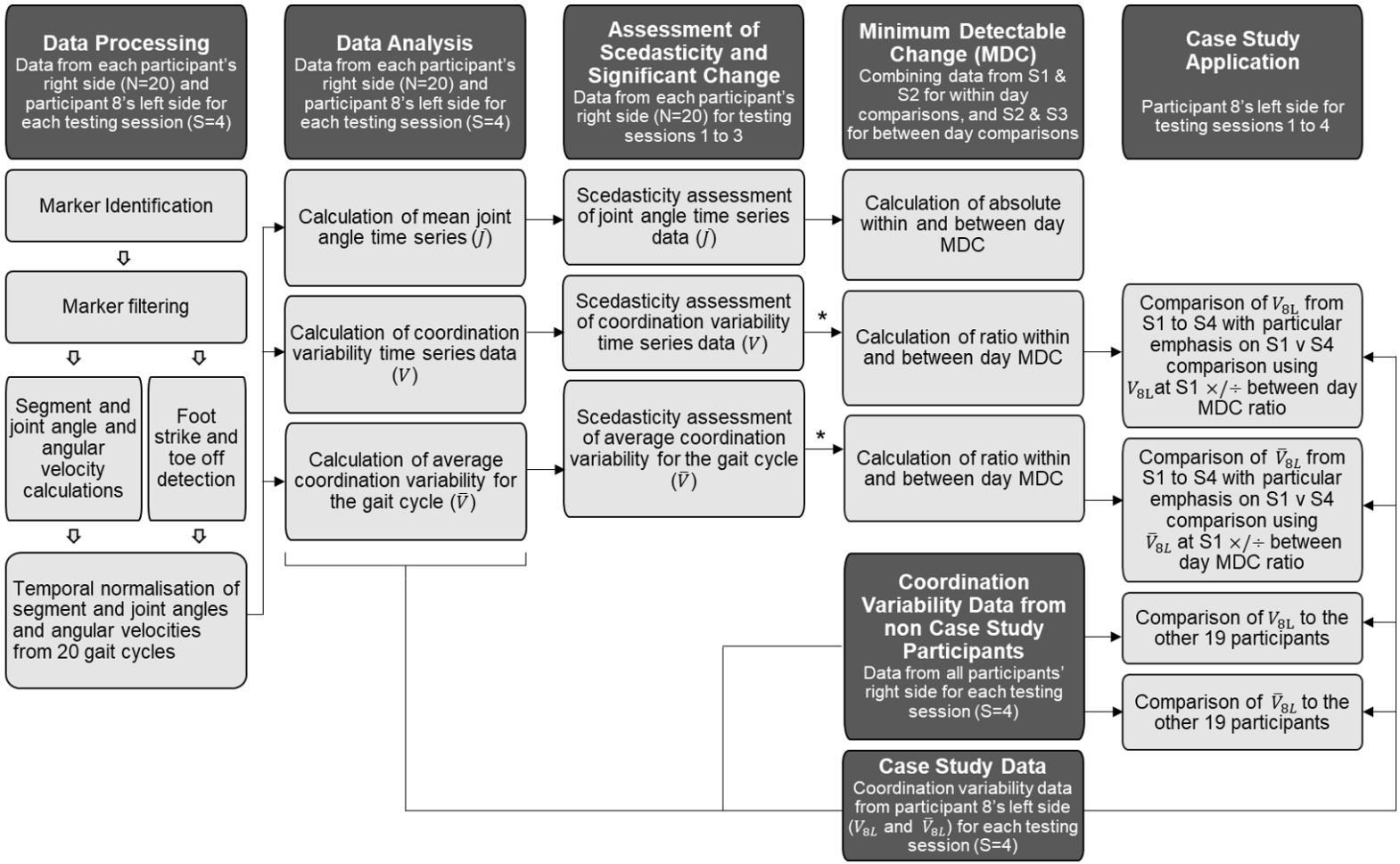


Figure 5.6. Schematic of data analysis process for Chapter 5. S1 S2, S3 and S4 represent the four data collection sessions. Subscript $_{8L}$ represents data from the left side of the case study participant which was the data analysed as part of the case study. The * represents that the data was observed to be heteroscedastic and became more homoscedastic following a log transform of the data. Consequently, alternative calculations were performed to compute the MDC as a ×/÷ ratio value instead of the more commonly seen ± absolute variant. The supporting results behind this choice can be found in the results section.

Table 5.3. Segment definitions in Visual 3D.

Segment	Proximal		Distal		Additional Notes
	Medial	Lateral	Medial	Lateral	
Pelvis					V3D_Composite Pelvis created which defines the pelvis segment using Anterior and Posterior Superior Iliac Spines for the left and right sides
Thigh	Hip		MFE	LFE	Hip landmarks created automatically in V3D when V3D_Composite pelvis is defined, using estimates adapted from Bell et al. 1989 and Bell et al. 1990 *https://www.c-motion.com/v3dwiki/index.php?title=V3D_Composite_Pelvis
Shank	MFE	LFE	TAM	FAM	
Foot	TAM	FAM	1FM	5FM	to create this segment, markers were projected onto the XY plane so that the foot was considered parallel with the floor in the standing trial. The coordinate system of the foot was then rotated so that its Z-axis was vertical

*** N.B. Marker abbreviations in this table are defined in Table 5.1**

(Handsaker et al., 2016). All exported variables were stored as separate columns of a matrix (**A**), where each row represented a separate frame of data (f). The heel, fifth metatarsal and toe marker trajectories were used as inputs to a foot-contact algorithm (Handsaker et al., 2016) which was modified to identify to identify the frame index of 21 consecutive foot strikes (α) and 20 toe-offs (β). The proposed algorithm first defined a window within which touchdown occurred by finding the anteroposterior velocity of the heel marker dropped below 1.5 ms^{-1} and ended at the next local minima in vertical heel position. The algorithm was developed for over ground running therefore in this chapter, the 1.5 ms^{-1} threshold was modified to 0 ms^{-1} to account for the use of the treadmill. Touchdown was defined as the first peak to occur in the vertical acceleration of either the heel (for a rearfoot strike) or the 5^{th} metatarsal marker trajectory to account for fore, mid and rear foot strikers. The validation study reported an offset of +3.1 ms with a 95% confidence interval of -11.8 to +18.1 (Handsaker et al., 2016). The toe-off window started 100 ms after touchdown and ended when the vertical toe position exceeded 0.1 m or reached a local maximum. Toe-off was defined as the peak in vertical jerk of the toe marker. Local peaks were identified using the MATLAB file exchange 'peakfinder' function (Yoder, 2011).

The following steps were computed for the data from each participant in each session: Matrix **A** was separated into 20 gait cycles (c = 1,…,20) using the frame indexes defined in $\widehat{\alpha}$, where $\widehat{\alpha}$ includes ($\in$) a series of vectors that reference the frame indexes from foot strike (α_c) to the final frame before the subsequent foot strike (α_{c+1}):

$$\mathbf{B}_c = \mathbf{A}[\widehat{\alpha}_c] \qquad \widehat{\alpha}_c \in \left[\alpha_c, \alpha_c + 1, \alpha_c + 2 \ \ldots \alpha_{c+1}\right] \tag{5.1}$$

The resulting output was a collection of 20 matrices ($\mathbf{B}_c$) of varying length containing the joint and segment angle and angular velocity data from each gait cycle. The percentage of each gait cycle that was spent in the stride cycle (ζ) was also computed:

$$\zeta_c = \frac{\beta_c - \alpha_c}{\alpha_{c+1} - \alpha_c} \tag{5.2}$$

And the mean percentage of gait spent in the stance phase ($\bar{\zeta}$) across C = 20 gait cycle repetitions was calculated:

$$\bar{\zeta} = \frac{\sum_{c=1}^{C} \zeta_c}{C} \tag{5.3}$$

Matrices $\mathbf{B}_c$ were then temporally registered. The average number of motion capture frames per gait cycle over all participants and trials was 142 (minimum 123, maximum 157). Spline interpolation was used to temporally register segment and joint data from each stride cycle to 101 temporal nodes (t); 0% to 100% of the stride cycle. The first temporal node represented 0% of gait when the ipsilateral side contacted the treadmill. The 101st temporal node represented 100% of gait and was the first frame that the ipsilateral foot next re-contacted the treadmill. A total of 20 stride cycles (C) were included for the analysis.

The data from the right lower-limb side was processed for calculating group minimum detectable changes. Data from the left side of the case study participant were also processed using the same methods.

5.2.5 Data Analysis

Coordination Variability Time Series and Average Values

Four coordination variability couplings were chosen for coordination variability analysis based on their popularity in vector coding coordination literature (Table 5.4). Those couplings were (1) thigh flexion/extension – shank flexion/extension (2) shank internal/external rotation

– foot eversion/inversion (3) hip flexion/extension – knee flexion/extension (4) knee flexion/extension – ankle eversion/inversion.

The velocity ellipse method was applied, as described in Chapter 4, to calculate coordination variability (V) for couplings: T_{FE}-S_{FE}, S_{IER}-F_{IE}, H_{FE}-K_{FE}, K_{FE}-A_{IE} using angular velocity (ω) variables as the inputs to equations. In brief, this involved the following calculation steps based on similar methods presented by Duarte and Zatsiorsky (2002) and Mullineaux (2017):

1) A covariance matrix [2 2] was formed from ω_x and ω_y at each temporal node (Equations 4.7 and 4.8)

2) Eigenvalues were computed from each covariance matrix (Equations 3.9 to 3.13)

3) Ellipse axes were formed from the root of each eigenvalue scaled according to *k* (Equation 3.14 and 3.15), so that the size of the ellipse was not affected by the number of stride cycles collected (Schubert and Kirchner, 2014; Mullineaux, 2017).

4) The product of the ellipse axes was multiplied by pi to define an ellipse area (V) about the mean data point within which 95% of future observations should fall (Equation 3.16). Ellipse area served as the measure of coordination variability: the greater the area of the ellipse the more variable the coordination variability was.

Coordination variability (V) was then averaged across the entire gait cycle (indexed by t = 1,…,101) to calculate average coordination variability ($\bar{V}$) for each participant in each session:

$$\bar{V} = \frac{\sum_{t=1}^{T} V_t}{T} \tag{5.4}$$

This provided a single metric by which a participant could be judged to have high or low variability compared to other participants or from one session to the next.

Mean Joint Angle Time Series

The joint angles selected for analysis (Table 5.2) corresponded to the joint angles which comprised the coordination couplings chosen for investigation: hip flexion/extension (H_{FE}), knee flexion/extension (K_{FE}) and ankle inversion/eversion (A_{IE}). Ankle dorsi/plantar flexion (A_{DP}) was also included to give a more complete picture of lower-limb movement in the sagittal plane. The arithmetic joint angle means ($\bar{J}$) were calculated across the gait cycle repetitions (c = 1,…,20) for each participant, at each normalised time point, in each of the four data collection sessions:

Table 5.4. Prevalence of the four coordination variability couplings analysed in this chapter in publications of injury related research in gait. T_{FE}-S_{FE}: thigh flexion/extension – shank flexion/extension, S_{IER}-F_{IE}: shank internal/external rotation – foot eversion/inversion, H_{FE}-K_{FE}: hip flexion/extension – knee flexion/extension, K_{FE}-A_{IE}: knee flexion/extension – ankle eversion/inversion

Coupling	Research examples using this coupling	Injury type investigated / referred to in research justification
T_{FE}-S_{FE}	Boyer, Silvernail and Hamill (2017)	Generic running injuries
	Whited et al. (2013)	Generic running injuries
	Silvernail et al. (2015)	Generic running injuries
	Bonacci et al. (2020)	PFP
	Jewell (2018)	PFP
	Whited et al. (2014)	Hip replacement surgery
S_{IER}-F_{IE}	Hafer, Brown and Boyer (2017)	IT band
	Ferber and Pohl (2011)	Tibialis posterior
	MacLean, van Emmerik and Hamill (2010)	Overuse running injuries at the knee
	Ferber, Davis and Williams (2005)	Running related injuries
	Hafer et al. (2016)	Overuse injuries
	Herb, Chinn and Hertel (2016)	CAI
	Herb et al. (2014)	CAI
	Boyer, Silvernail and Hamill (2017)	Generic running injuries
	Takabayashi et al. (2018a)	Running injury at the knee
H_{FE}-K_{FE}	Samaan et al. (2015b)	Hip OA
	Samaan et al. (2015a)	ACL
	Floría et al. (2019)	Injury status
	Davis et al. (2019)	ACL
K_{FE}-A_{IE}	Cunningham (2012)	PFP
	Heiderscheit, Hamill and van Emmerik (2002)	PFP
	Dierks and Davis (2007)	Injury status
	Lilley et al. (2017)	CAI
	Floría et al. (2019)	Injury status

*** PFP – Patello femoral pain, IT band – Iliotibial band, CAI – Chronic Ankle Instability, ACL – Anterior Cruciate Ligament, OA – Osteoarthritis**

$$\bar{J} = \frac{\sum_{c=1}^{C} J}{C} \tag{5.5}$$

5.2.6 Repeatability Specific Methods

The methods of estimating repeatability used in this thesis are largely based on the techniques suggested by (Bland and Altman, 1996a). The minimum detectable change (MDC) also referred to elsewhere as the 'smallest worthwhile difference' (Beckerman et al., 2001) is the same measure that Bland and Altman first referred to as 'repeatability'. The MDC was chosen as it calculates a range of values within which 95% of the differences between two measurements (taken on the same person under the same conditions) should fall within. Thus, if the difference between two measurements does not exceed the upper or lower boundary of the MDC, the difference can be assumed to be a result of random fluctuations. The MDC therefore represents how much change might be methodologically meaningful to detect, but further work would be required to determine what value is of clinical significance.

To calculate the MDC a minimum of two repeated measures are required that were taken under the same conditions in a sample population. For the MDC calculations to be valid, it is important to first check that no systematic changes occurred within the group between those sessions. The next step is to understand whether the within participant variance between the repeated sessions is consistent or varies across a range of values (the scedasticity). The scedasticity of the data is important as it determines the most appropriate methods to calculate the MDC. The exact methods used to perform these steps within this chapter were as follows:

Systematic Changes

Possible systematic changes were checked by performing statistical non-parametric mapping (SnPM) repeated measures Analysis Of Variance (ANOVA) tests for both discrete and time-series data using open source code (Pataky, 2019). When data inputted to these statistical procedures are parametric, results from SnPM converge with those of Statistical Parametric Mapping (SPM). SnPM was therefore used to avoid the assumption of a parametric distribution. Specifically, SnPM was performed for each dependent variable (Table 5.2) using data for all twenty participants, with session as the repeated measure (S1, S2 and S3). A t statistic was computed for the discrete data and a t-statistic trajectory was computed for each temporal node of the time-series data. The permutation method (Nichols and Holmes, 2002) summarised comprehensively in Pataky, Vanrenterghem and Robinson (2015) was used to generate the tcrit-threshold statistic (F*) from 10,000 permutations (α =0.05). When the t statistic exceeded this threshold, individual probabilities were calculated for the likelihood

that the result could have been generated by a random process. This approach is based on Random Field Theory (Adler and Taylor, 2007). Due to short time periods between sessions one to three no significant changes were expected to occur between any of the three sessions.

Scedasticity

Scedasticity refers to the distribution of error terms. When error terms are distributed randomly with constant variance, the spread of the error terms is referred to as homoscedasticity. Heteroscedasticity is when error terms are not equal across the range of values. If the error terms of a dataset are heteroscedastic, traditional parametric statistical assumptions can be violated and alternative statistical approaches may be necessary. In the specific instance of repeatability investigations with two repeated measures, if data is homoscedastic then the absolute differences observed between repeated measurements would be the same, regardless of the magnitude of the measurements. Thus, any indicator of expected variation between repeated measurements can be expressed as ± about the measured value. In heteroscedastic data the relationship between the absolute difference between measurements and the mean value can take many different forms, but one of the most commonly seen in sport science is that the absolute difference between measurements is greater for larger values (Atkinson and Nevill, 1998). In these circumstances, it is therefore not appropriate to have a fixed ± variation applied to all values, and so expected variation must be represented as a ratio. Any value of the measured data is multiplied by the ratio to estimate the upper limit of the expected variation or divided by the ratio to estimate the lower limit of expected variation. The ratio is therefore represented as × / ÷ instead of ± and has a minimum possible value of one. A ratio of one would indicate perfect repeatability of the measurement.

To check whether a dataset of repeated measures demonstrated homo- or hetero-scedastic properties and determine the most appropriate method for calculating the MDC for each dependent variable, a process of steps was followed (Figure 5.7). The process was largely based on the methods presented in Bland and Altman (1996a) and (Bland and Altman, 1996b) and further details of the individual steps and calculations are provided later in the chapter. There are a number of examples within sport science research where the methods presented by Bland and Altman have been applied to discrete measures, but there is little or no advise for its application to time series data. In this chapter, the scedasticity of time series data was assessed by combining all temporal nodes of the time series into a single dataset.

Decision of constant variance

A combined qualitative and quantitative approach was used to decide whether the spread of variance was consistent across the range values measured in the process of assessing the

scedasticity of each dependent variable (Figure 5.7). The qualitative approach was to visually assess whether the within participant differences between sessions were constant across all within participant mean values (e.g. simulated example data in Figure 5.8A) or if they were not consistent across the range of values (e.g. simulated example data in Figure 5.8B). In the quantitative approach, a Kendall rank correlation test was performed (Kendall, 1938; Bland and Altman, 1996b). The Kendall rank test ranks each observation for each variable (in this example, one list of ranking for the within participant mean, and another for the within participant between session difference). The Kendall correlation (τ) is high (a maximum of 1) when each observation has the same or similar rank for both variables, low (a minimum of -1) when the ranks for each variable are opposite and 0 when there is no correlation between the ranks. A *p* value was also calculated to determine if the correlation is significant ($\alpha < 0.05$).

Homoscedastic data would be expected to have a non-significant τ value close to 0 (e.g. τ = -0.01 and p = 0.66 for the simulated data in Figure 5.8A). The inclusion of the qualitative approach is important as the Kendall Rank test is only appropriate for testing linear correlations.

Calculation of the minimum detectable change

The appropriate steps for calculating the MDC depend on whether the data are homoscedastic either in their raw form or following a $\log_{10}$ transform. Data that is homoscedastic in its raw form can be used to calculate an MDC. This MDC can then be used to interpret whether an observed difference between two new measurements (M1 and M2) is meaningful. The absolute MDC is added to and subtracted from M1 to create a range within which future repeated measurements could be expected to fall (e.g. Figure 5.9A). Conversely, data that is not homoscedastic in its raw form but is following a $\log_{10}$ transform must be processed in a different way to calculate an MDC ratio. M1 is multiplied by the MDC ratio to create the upper boundary of the MDC and divided by the MDC ratio to create the lower boundary about M1. This also creates a range within which future measurements could be expected to fall but the range expected above a measurement is greater than the range expected below, and greater variance is expected for measurements of larger magnitudes (e.g. Figure 5.9).

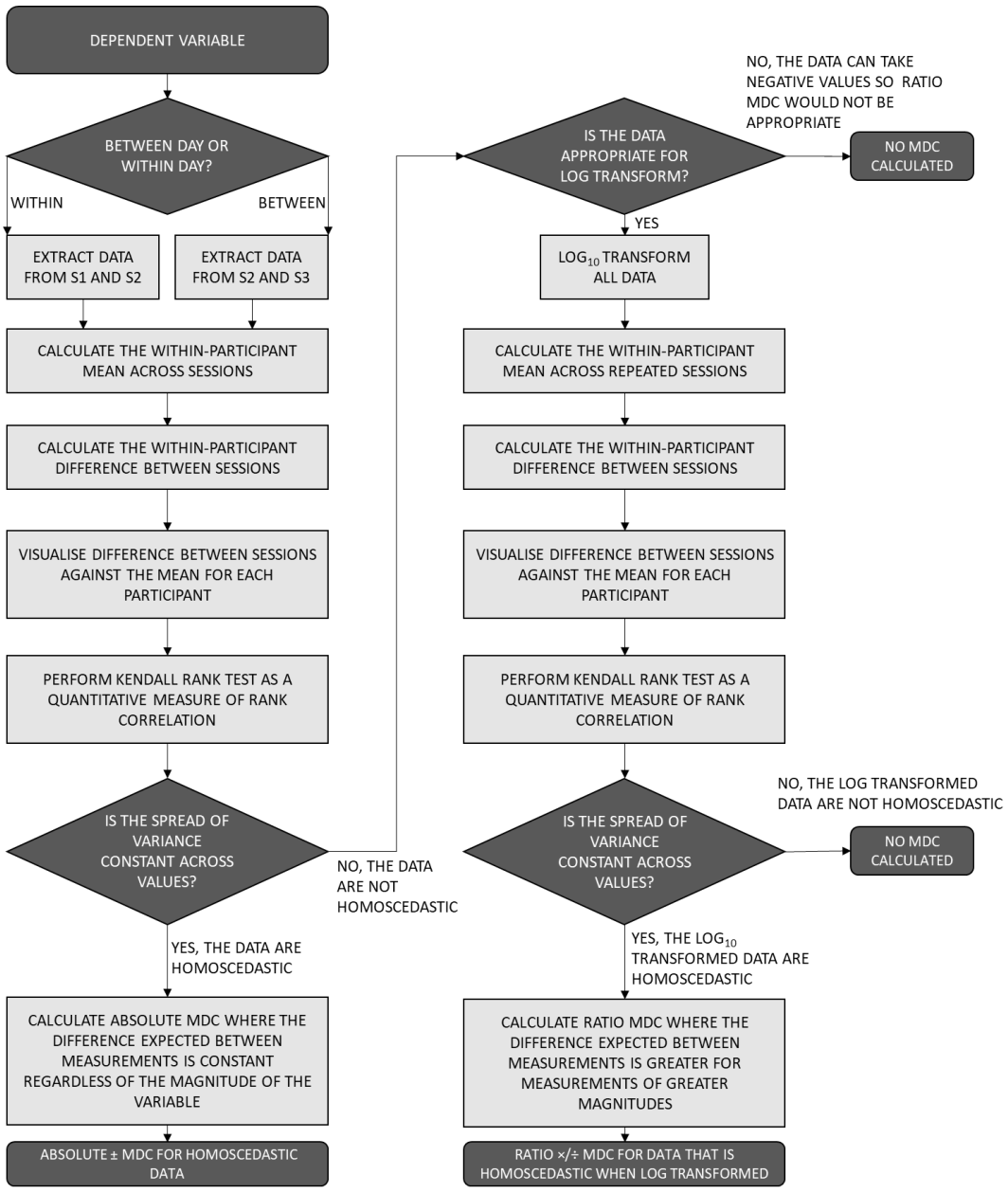


Figure 5.7. Flow diagram of the steps and decision processes taken to identify the scedasticity of the repeatability data and the appropriate method for calculating the Minimum Detectable Change (MDC).

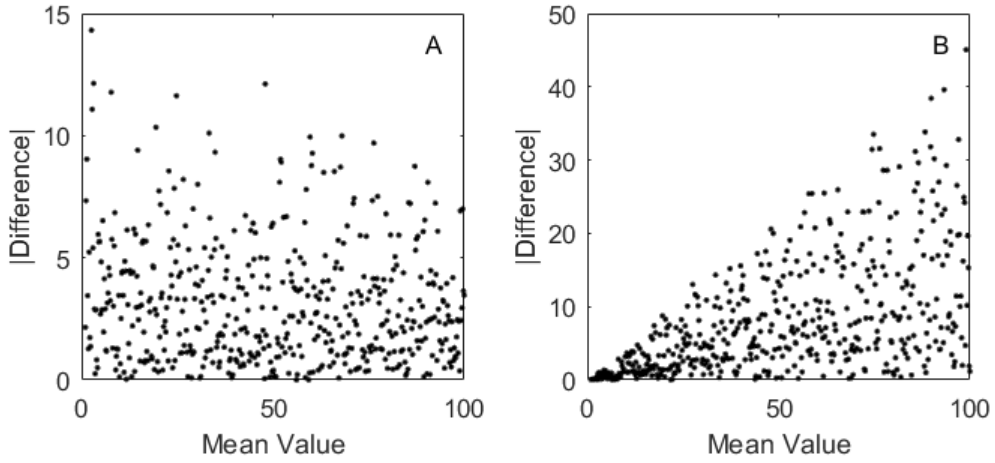


Figure 5.8. Examples of homoscedastic (A) and heteroscedastic (B) data. In the homoscedastic data, the absolute differences between repeated measures remain constant across the entire range of mean values. In the heteroscedastic example the mean absolute difference is not constant across the range of mean values. In this example the absolute differences start small and increase as the mean value becomes larger. The example data in A was simulated by extracting random numbers from a normal distribution.

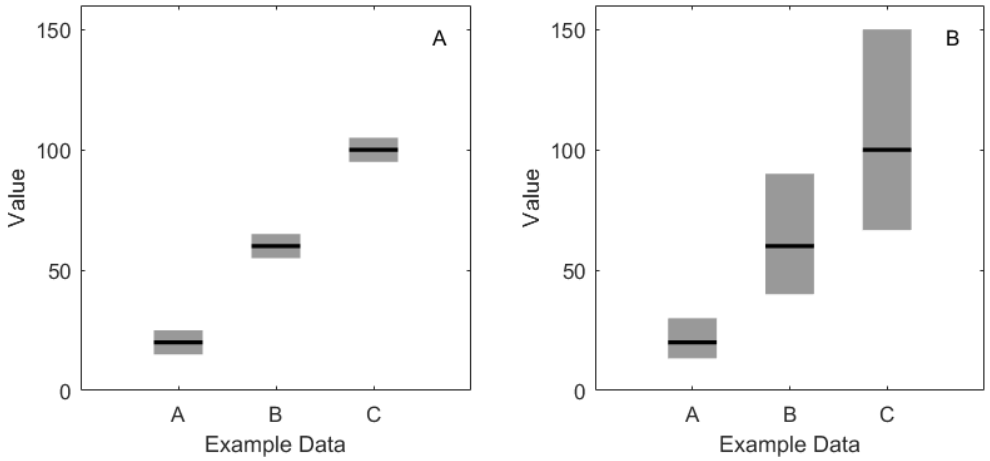


Figure 5.9. Example application of an absolute Minimum Detectable Change (MDC) compared to an MDC ratio. A) An absolute MDC of ± 5 (grey shaded areas, subplot A) applied to three pieces of example data (A = 20, B = 60, C = 100, indicated with black lines). B) An MDC ratio of ×/÷ 1.5 (grey shaded area, subplot B) applied to the same example data as in A. If a second measurement were taken for example data A, B and C, was plotted on the same graphs, and was situated within the shaded MDC area, the difference between those two measurements is likely to be the result of fluctuations in the measurement. If the second measurement exceeded the shaded areas in a positive/negative direction this would suggest that a change was observed which was greater than the fluctuations that we expect to observe in the measurement.

Homoscedastic Data

For homoscedastic data a ± MDC value (MDCV) was calculated for the within day (session 1 and session 2) and between day (session 2 and session 3) comparisons for each time point (Bland and Altman, 1996a). This has been demonstrated for the specific example of the within day (WD) joint angle measurements ($\bar{J}$), where the MDCV is calculated across the participant group (p = 1,…,20), S1 represents data from session 1 and S2 represents data from session 2:

$$MDCV_{WD} = 1.962 \cdot \sqrt{2} \cdot \sqrt{\frac{\sum_{p=1}^{P=20}(\bar{J}_{S2,p} - \bar{J}_{S1,p})^2}{2P}} \tag{5.6}$$

To use the *MDCV* in practice, a baseline measurement is collected ($\overline{J'}$), an intervention is conducted and another measurement is taken ($\overline{J''}$). The user wishes to understand whether the change they observed between $\overline{J'}$ and ($\overline{J''}$) is greater than the minimum detectable change. The *MDCV* can then be used to calculate upper and lower MDC boundaries about $\overline{J'}$ (Equation 5.7 & 5.8). If $\overline{J''}$ is greater than the upper boundary or less than the lower boundary, then the change observed was greater than the minimum detectable change.

$$UpperMDC = \overline{J'} + MDCV \tag{5.7}$$

$$LowerMDC = \overline{J'} - MDCV \tag{5.8}$$

Homoscedastic Data following log transform

In cases where the log transformed data was found to be homoscedastic, MDC ratio (*MDCR*) was calculated for the within day (session 1 and session 2) and between day (session 2 and session 3) comparisons based upon calculations presented in Bland and Altman (1996a) and (Bland and Altman, 1996b). This process has been demonstrated for the specific example of between day (BD) coordination variability time series measurements (V) in (Equations 5.10 to 5.12). The equations were all applied to each time point of the time series data. The first step was to $\log_{10}$ transform all data for each participant in each session:

$$\hat{V} = \log_{10}(V) \tag{5.9}$$

and use the transformed data as an input for calculating the standard error of measurement of the log transformed data ($\hat{S}$) across the participant group using data from session 2 (S2) and session 3 (S3).

$$\hat{\mathrm{S}}_{BD} = \sqrt{\frac{\sum_{p=1}^{P=20}(V_{\mathrm{S3},p} - V_{\mathrm{S2},p})^2}{2P}} \tag{5.10}$$

The standard error of measurement of the log transformed data ($\hat{S}$) was then inverted to transform from the logarithmic scale back to the natural scale:

$$\sigma_{g_{BD}} = 10^{\hat{\mathrm{S}}_{BD}} \tag{5.11}$$

This process outputs a ratio that can be referred to as the geometric standard deviation (σ_g). Bland and Altman then manipulated σ_g to encompass 95% of the data by raising $\sigma_g$to the power of 1.96 (Bland and Altman, 1996b). In this thesis this step of the method has been extrapolated to the context of the MDC measure by raising σ_g to the power of $1.96 \cdot \sqrt{2}$ (Equation 5.12). This accounted for encompassing 95% of the differences between two measures.

$$MDCR_{BD} = (\sigma_{g_{BD}})^{1.96 \cdot \sqrt{2}} \tag{5.12}$$

To use the MDCR in practice, a baseline measurement is collected (V'), an intervention is conducted, and another measurement is taken (V''). The user wishes to understand whether the change they observed between V' and V'' is greater than the minimum detectable change. The MDCR can then be used to calculate upper and lower MDC boundaries about V' (Equation 5.13 & 5.14). If V'' is greater than the upper boundary or less than the lower boundary, then the change observed was greater than the minimum detectable change.

$$UpperMDC = V' \cdot MDCR \tag{5.13}$$

$$LowerMDC = \frac{V'}{\mathrm{MDCR}} \tag{5.14}$$

5.2.7 Case Study Specific Methods

Data from the case study example were used to make within participant comparisons across the longitudinal data collected. The calculated MDCs were used in conjunction with this data to add context to the magnitude of changes observed within the participant between sessions.

Comparisons were also made to the data collected from the other 19 participants to understand whether the case study participant had especially high or low coordination variability compared to the group. This was achieved by creating a distribution of data from the 19 participants right legs containing data from all four sessions and visualising the case study participant's data in comparison to the distribution created from the rest of the group. The case study participant's data from their left leg (the leg in which pain was reported) was then compared to the distribution created from the other participants using violin and box plots for the average coordination variability data, and by graphically representing the percentiles ranges in the coordination variability time series data. The case study participant's coordination variability was considered high or low in relation to the comparison population if it was lower than the 10^{th} or higher than the 90^{th} percentile.

5.3 Results

5.3.1 Retention and Timing of Data Collection Sessions

All participants were able to attend each of the four data collection sessions. The average time between the first session and the second was 3hr 15 minutes ± 5 minutes, the third 7 ± 1 day and the fourth was 56 ± 2 days. The third and fourth sessions took place within the same half of the day (pre or post 1pm) as session one had, in all but four cases for each session (P14, P11, P19, P15 at T3, P13 P18 P9 and P10 for T4).

5.3.2 Pain Scores

Fourteen of the twenty runners recruited remained pain free between the first and third testing sessions (Table 5.5). Of the six who were not pain free, three of the participants reports of pain were due to delayed onset muscle soreness (DOMS). The remaining three reported feeling pain in their lower back (rated 1 or 2 on a scale of 5).

5.3.3 Case Study Participant Selection

Within the design of the study a case-study was not identified *a priori* as it was not possible to know if any of the participants would experience pain or injury at the fourth data collection session or between the third and fourth sessions. The self-reported injuries and sources of pain were therefore reviewed once all the data had been collected. Four of the twenty participants reported that they had experienced some form of pain or injury in the period between testing

sessions (P1 P3 P5 and P9) but no longer felt any pain. A further three participants indicated that they were experiencing pain at the time of the fourth data collection session (P7 P8 P11). Participants 7 and 11 rated the pain they were experiencing as 1 which was the lowest possible rating indicating only mild discomfort. Participant 8 was selected as the single case study example to be presented within this thesis because they reported the highest pain rating within the whole data collection process (a rating of 4 out of 5) and were experiencing the pain at the time of testing (Table 5.5).

5.3.4 Repeatability Analysis

Data assumption tests

The MDC calculations are only valid when calculated on data where no significant change has occurred between the repeated sessions. Additionally, the way in which MDC is calculated depends on the scedasticity of the within day (session 1 vs session 2) or between day (session 2 vs session 3) variance. The following sections report whether significant changes occurred between sessions one, two and three, and report whether each subset of dependent variables are homo or heteroscedastic to inform.

Table 5.5. Pain ratings and areas of pain in the lower limb over the testing period. Green indicates no pain, yellow a pain score of 1, gold a pain score of 2, orange a pain score of 3 and red a pain score of 4 for the source of pain stated in each respective row. This was rated on a Likert scale of 1 to 5 where 1 represented 'slightly uncomfortable' and 5 represented 'very painful'. A pain rating of 5 was not recorded at any point. Participants were also asked to state if they had experienced any injuries between testing sessions and these reports are stated in the interim periods.

	Self reported pain	S1	S2	~ 1 week interim	S3	~ 7 week interim	S4
P1 (F)						Pain in top of right foot, 2.5 weeks before	
P2 (F)							
P3 (F)	DOMS in quads					Pain in bottom of left foot (ligament/tendon)	
P4 (F)							
P5 (F)	Right knee pain					Sacro iliac joint discomfort after running >7km	
P6 (F)							
P7 (F)	Right knee pain						
P8 (F)	DOMS in calves						
	Left heel pain						
P9 (F)						Left shin pain reported following half marathon	
P10 (F)							
P11 (M)	Right hip pain						
	Mid calf pain						
	Right knee pain						
P12 (M)	Left lower back						
	Right 5th metatarsal						
P13 (M)							
P14 (M)	Left achilles pain						
P15 (M)							
P16 (M)							
P17 (M)	DOMS in hips						
	DOMS in thighs						
	DOMS in calves						
	Lower back pain						
P18 (M)							
P19 (M)							
P20 (M)							

Coordination variability averaged across the gait cycle

The SnPM repeated measures ANOVA did not identify significant group changes between sessions one, two and three for the average coordination variability metrics ($\bar{V}$) in any of the four coordination coupling pairs (Table 5.6).

Table 5.6. SnPM repeated measures ANOVA (α = 0.05) for coordination variability averaged across the gait cycle ($\bar{V}$). Mean ± standard deviation at session 1 (S1), session 2 (S2) and session 3 (S3) and *p* values are reported for the following couplings: thigh flexion/extension – knee flexion/extension (T_{FE}-S_{FE}), Shank internal/external rotation – foot inversion/eversion (S_{IER}-F_{IE}), Hip flexion/extension – knee flexion/extension (H_{FE}-K_{FE}) and Knee flexion/extension – ankle inversion/eversion (K_{FE}-A_{IE}).

Coupling	$\bar{V}$ at S1 ($^{\circ 2}\cdot s^{-2}$)	$\bar{V}$ at S2($^{\circ 2}\cdot s^{-2}$)	$\bar{V}$ at S3 ($^{\circ 2}\cdot s^{-2}$)	*p value*
T_{FE}-S_{FE}	4600 ± 1900	4600 ± 1900	4100 ± 1500	0.325
S_{IER}-F_{IE}	13800 ± 6600	13600 ± 4100	12100 ± 3400	0.078
H_{FE}-K_{FE}	7000 ± 2800	7200 ± 3200	6600 ± 2100	0.467
K_{FE}-A_{IE}	12400 ± 5700	1200 ± 4100	11000 ± 3500	0.107

The small number of data points made it challenging to judge the relationship between the within and between day mean average coordination variability ($\bar{V}$) values and their differences (Figure 5.10). The Kendall rank tests indicated correlations (τ) of between 0.200 and 0.463, some of which were significant (α<0.05, Figure 5.10). Consequently, $\bar{V}$, were then log transformed. Following the log transform, the data appeared more homoscedastic (Figure 5.11). Kendall rank test correlations then ranged from 0 to 0.126 and no *p* values were significant. The more homoscedastic patterns following log transform informed the decision to proceed using log transformed data for all average coordination variability metrics.

Coordination variability time series

The SnPM 1D repeated measures ANOVA did not identify any significant group changes between any of the first three sessions for the coordination variability time series (Figure 5.12).

Visually the mean value – absolute difference plots demonstrated heteroscedasticity in the coordination variability time series data and the Kendall rank correlations supported this with significant correlations of 0.385 to 0.466 (Figure 5.13). All data were therefore log transformed. The mean value – absolute difference plots of the log transformed data appeared homoscedastic. This was supported by the Kendall rank correlations of -0.032 to 0.050. Some significant *p* values were observed but this is not surprising given the large number of data points. Therefore, the log transformed time series were used for all further MDC analysis (Figure 5.14).

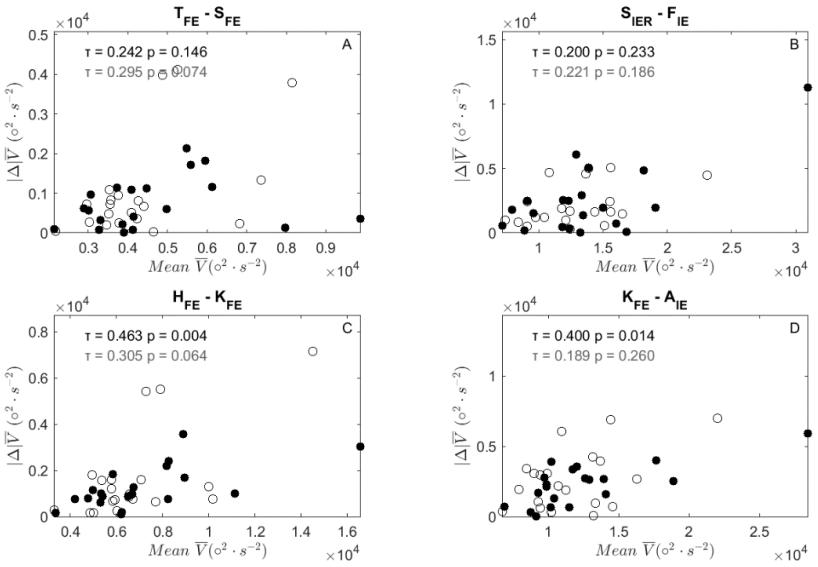


Figure 5.10. Assessment of the scedasticity of mean coordination variability across the gait cycle ($\overline{V}$). Mean $\overline{V}$ across sessions is plotted against the absolute difference ($|\Delta|$) in $\overline{V}$ between sessions for: sessions S1 and S2 (within day, filled circles, Kendall rank test results reported in black) and S2 and S3 (between day, unfilled circles, Kendall rank test results reported in grey). Each point is associated with an individual participant and the following couplings are reported: A) thigh flexion/extension – shank flexion/extension, B) shank internal/external rotation – foot internal/external rotation, C) hip flexion/extension – knee flexion/extension, D) knee flexion/extension – ankle inversion/eversion. Kendall rank test results are displayed where τ represents the strength of association and p indicates the statistical significance of the result to 3 decimal places.

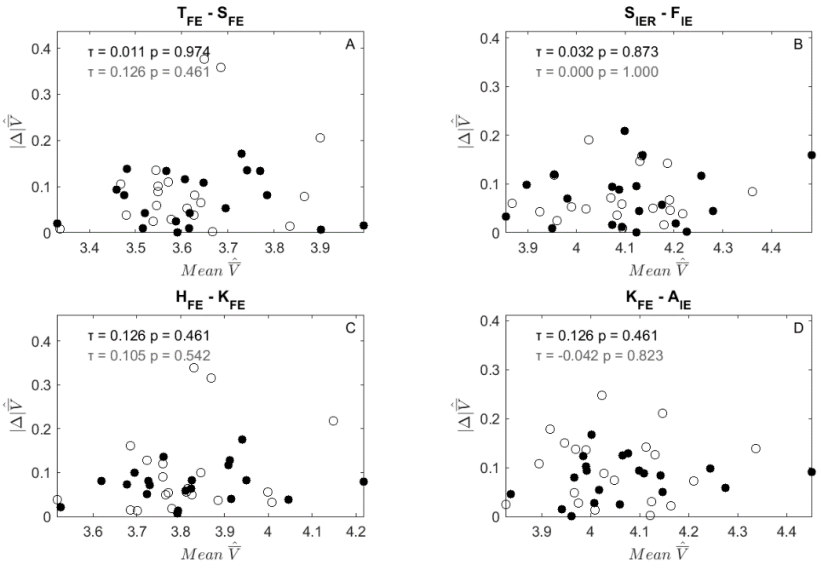


Figure 5.11. Assessment of the scedasticity of mean coordination variability across the gait cycle following log transform ($\hat{\overline{V}}$). Mean $\hat{\overline{V}}$ across sessions is plotted against the absolute difference ($|\Delta|$) in $\hat{\overline{V}}$ between sessions for: sessions S1 and S2 (within day, filled circles, Kendall rank test results reported in black) and S2 and S3 (between day, unfilled circles, Kendall rank test results reported in grey). Each point is associated with an individual participant and the following couplings are reported: A) thigh flexion/extension – shank flexion/extension, B) shank internal/external rotation – foot internal/external rotation, C) hip flexion/extension – knee flexion/extension, D) knee flexion/extension – ankle inversion/eversion. Kendall rank test results are displayed where τ represents the strength of association and p indicates the statistical significance of the result to 3 decimal places.

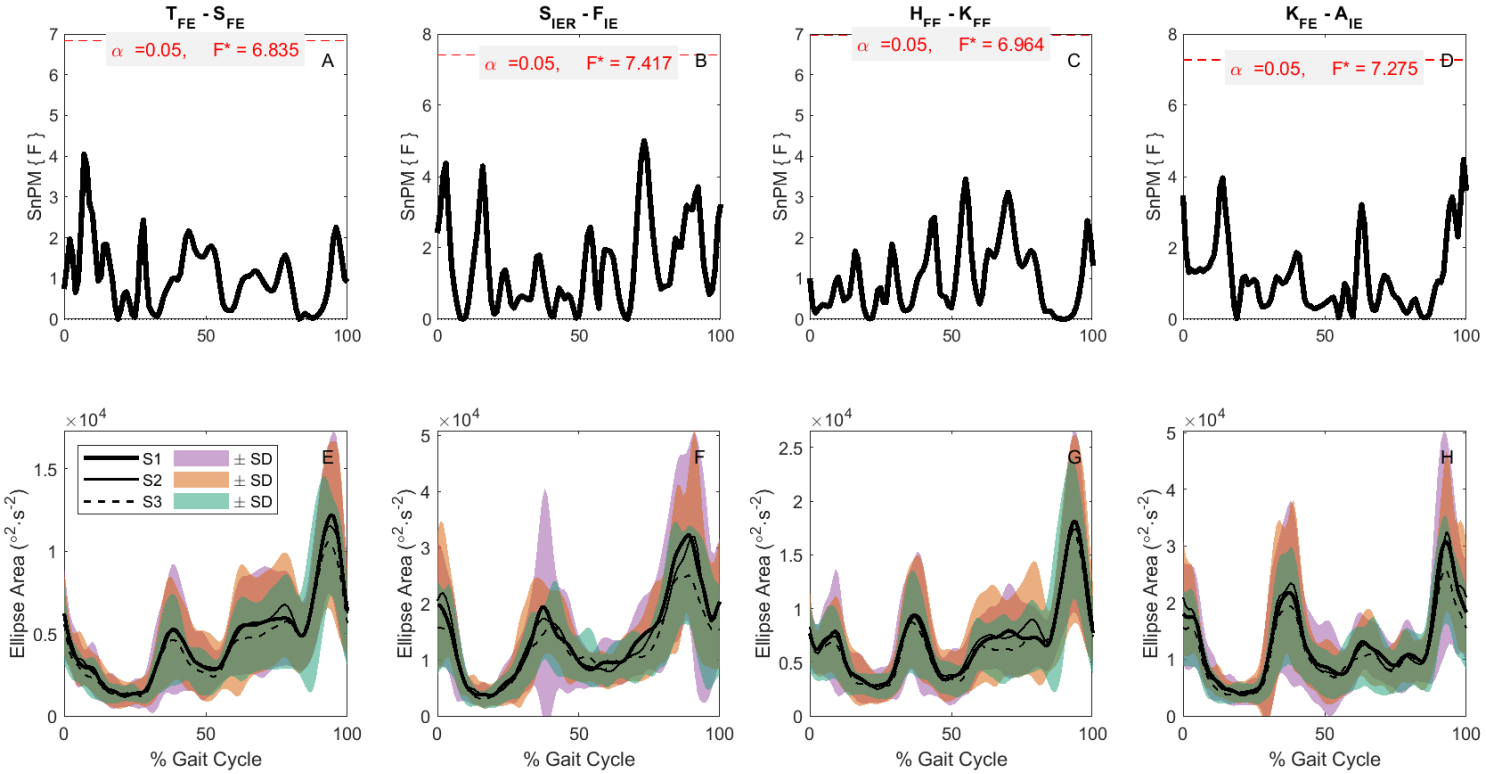


Figure 5.12. SnPM repeated measures ANOVA testing for significant differences between Session 1 (S1), Session 2 (S2) and Session 3 (S3) in coordination variability time series. The following couplings are reported: A & E) thigh flexion/extension – shank flexion/extension, B & F) shank internal/external rotation – foot inversion/eversion C & G) hip flexion/extension – knee flexion/extension D & H) knee flexion/extension – ankle inversion/eversion. On the top row, the black line represents the F statistic for each percentage of the gait cycle. The red dashed line represents the F* critical threshold for α = 0.05. In this instance the black line remains below the F* critical threshold which indicates that there was no statistically significant change detected between S1, S2 and S3 for any of the coordination variability couplings. The bottom row show the mean and standard deviation of coordination variability across participants in each session.

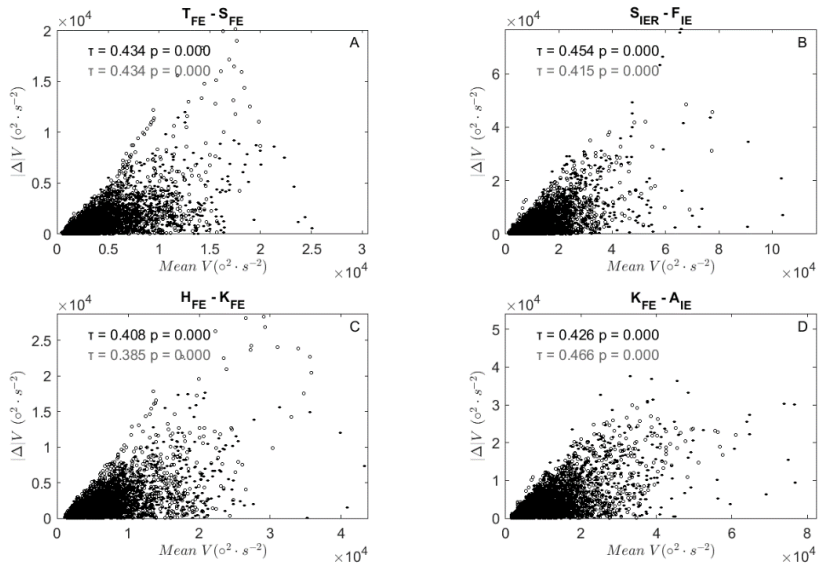


Figure 5.13. Assessment of the scedasticity of coordination variability (*V*) at each temporal node of the gait cycle. Mean *V* across sessions is plotted against the absolute difference (|Δ|) in *V* between sessions for: sessions S1 and S2 (within day, filled circles, Kendall rank test results reported in black) and S2 and S3 (between day, unfilled circles, Kendall rank test results reported in grey). Each point represents a different temporal node (1,…,101) for each participant and the following couplings are reported: A) thigh flexion/extension – shank flexion/extension, B) shank internal/external rotation – foot internal/external rotation, C) hip flexion/extension – knee flexion/extension, D) knee flexion/extension – ankle inversion/eversion. Kendall rank test results are displayed where τ represents the strength of association and p indicates the statistical significance of the result to 3 decimal places.

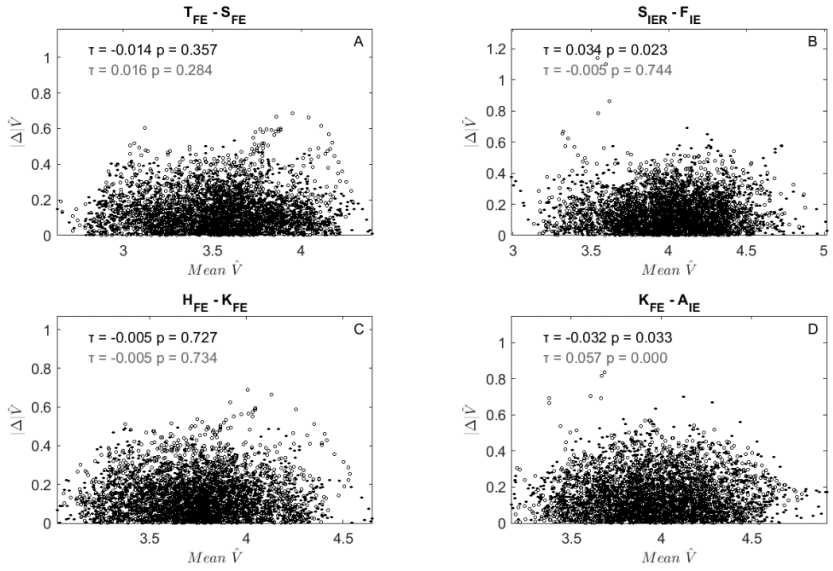


Figure 5.14. Assessment of the scedasticity of coordination variability following log transform ($\hat{V}$) at each temporal node of the gait cycle. Mean $\hat{V}$ across sessions is plotted against the absolute difference (|Δ|) in $\hat{V}$ between sessions for: sessions S1 and S2 (within day, filled circles, Kendall rank test results reported in black) and S2 and S3 (between day, unfilled circles, Kendall rank test results reported in grey). Each point represents a different temporal node (1…101) for each participant and the following couplings are reported: A) thigh flexion/extension – shank flexion/extension, B) shank internal/external rotation – foot internal/external rotation, C) hip flexion/extension – knee flexion/extension, D) knee flexion/extension – ankle inversion/eversion. Kendall rank test results are displayed where τ represents the strength of association and p indicates the statistical significance of the result to 3 decimal places.

Mean joint angle time series

No significant differences were observed between sessions one, two or three in the mean joint angle time series (Figure 5.15).

Visually, the mean value – absolute difference plots for joint angles suggested the joint angle measurements were homoscedastic (Figure 5.16). The Kendall rank correlations were also low (-0.153 to 0.172) and because joint angles can take negative values it would not be appropriate to calculate the MDC from log transformed data. Therefore a ± MDCV was calculated for all mean joint angle time series data

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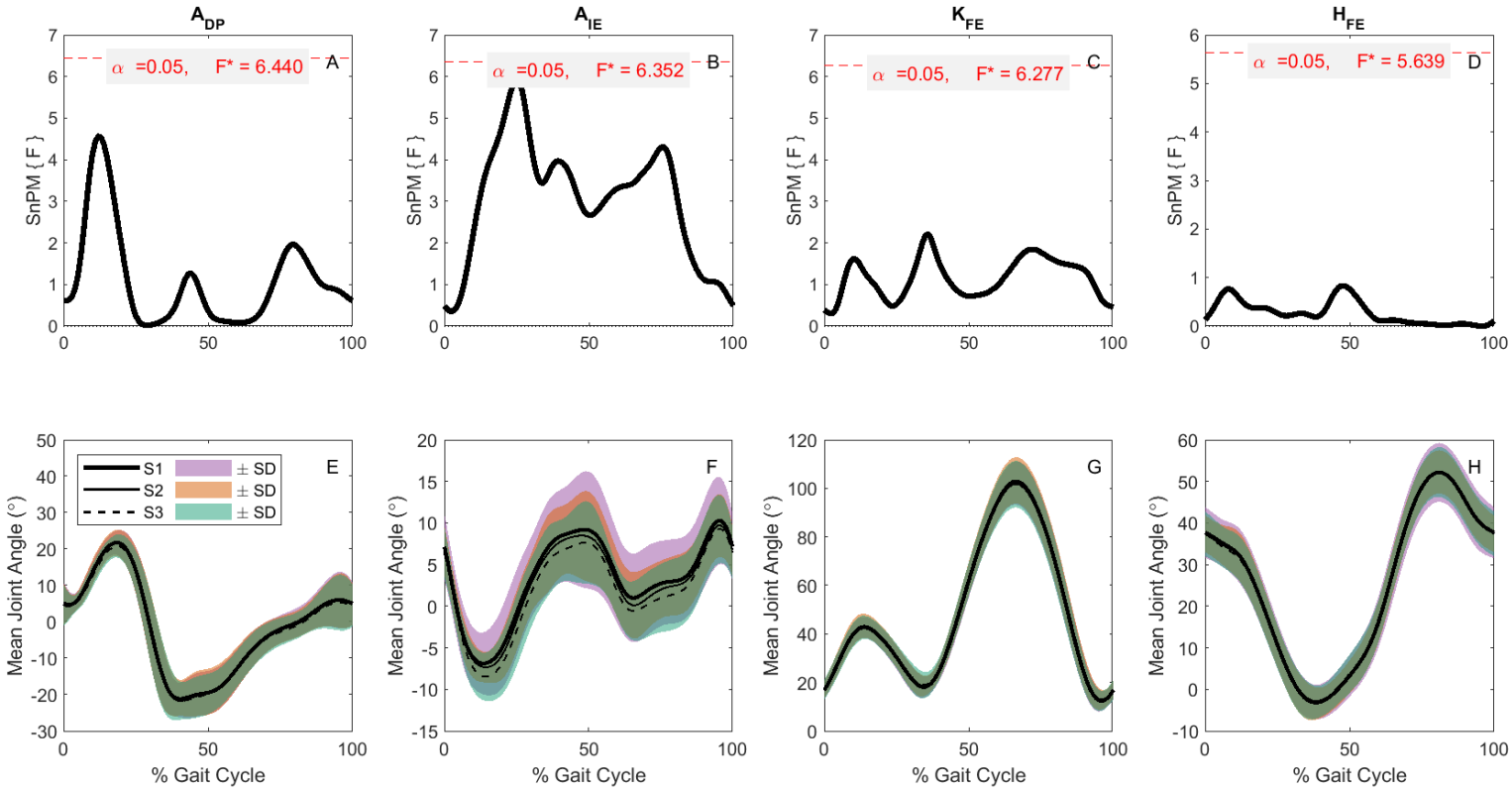


Figure 5.15. SnPM repeated measures ANOVA testing for significant differences between Session 1 (S1), Session 2 (S2) and Session 3 (S3) in mean (across cycle) joint angle time series. The following joint angles are reported A & E) ankle dorsi/plantar flexion, B & F) ankle inversion/eversion C & G) knee flexion/extension D & H) hip flexion/extension. In the top row, the black line represents the F statistic for each percentage of the gait cycle. The red dashed line represents the F* critical threshold for α = 0.05. In this instance the black line remains below the F* critical threshold which indicates that there was no statistically significant change detected between S1, S2 and S3 for any of the mean joint angle variables. The mean and standard deviation of each mean joint angle ($\bar{J}$) across the participants is reported on the bottom row of figures.

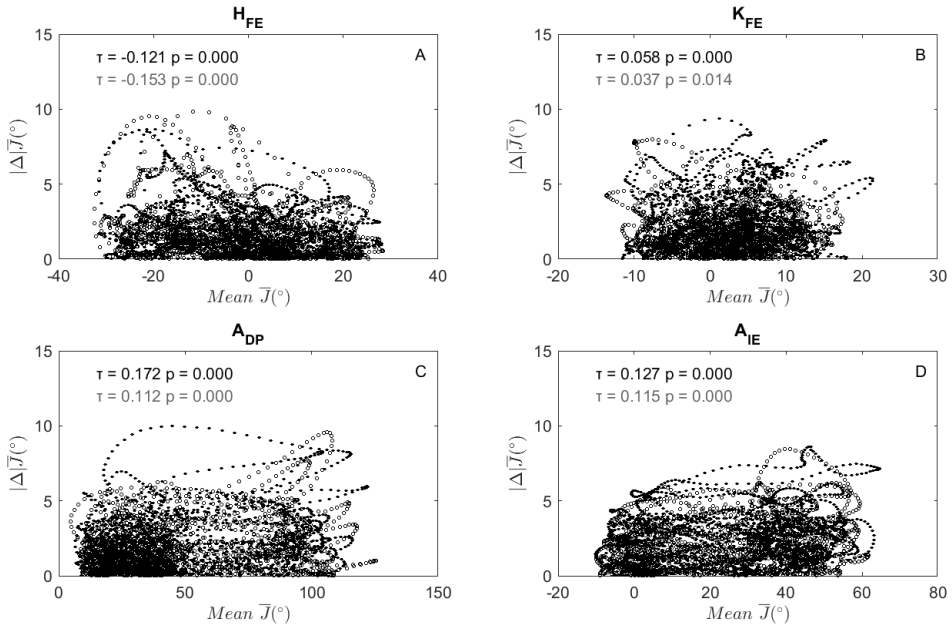


Figure 5.16. Assessment of the scedasticity of mean joint angle across gait cycles ($\bar{J}$) at each temporal node of the gait cycle. Mean $\bar{J}$ across sessions is plotted against the absolute difference (|Δ|) in $\bar{J}$ between sessions for: sessions S1 and S2 (within day, filled circles, Kendall rank test results reported in black) and S2 and S3 (between day, unfilled circles, Kendall rank test results reported in grey). Each point represents a different temporal node (1…101) for each participant and the following joint angles are reported: A) hip flexion/extension, B) knee flexion/extension, C) ankle dorsi/plantar flexion, D) ankle inversion/eversion. Kendall rank test results are displayed where τ represents the strength of association and p indicates the statistical significance of the result to 3 decimal places.

Minimum Detectable Change

Coordination Variability

The MDC ratios were generally higher for the between day than the within day comparisons for both average coordination variability across the gait cycle (Figure 5.17) and the time series coordination variability data (Figure 5.18). The largest difference in average coordination variability across the gait cycle was observed for thigh flexion/extension – shank flexion/extension where the MDC ratio was 0.40 higher for the between day comparison compared to within day. The MDC in shank rotation – foot inversion/eversion was 0.03 lower for the between day compared to within day (Figure 5.17). The smallest MDC ratio was 1.47 and greatest was 1.89 (Table 5.7).

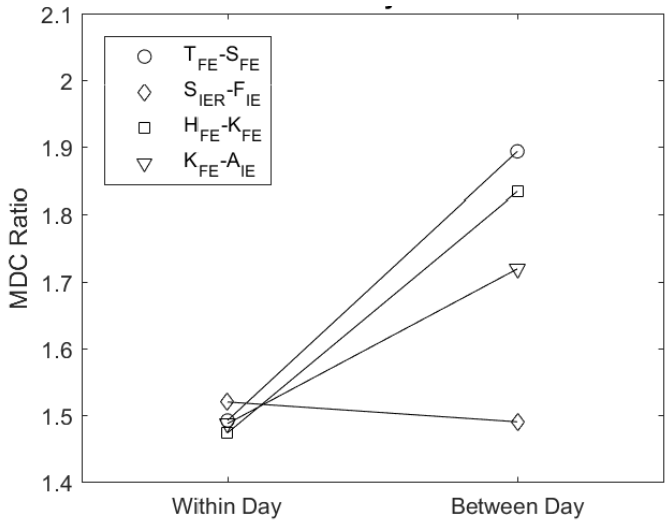


Figure 5.17. Within day (calculated using data from S1 and S2) and between day (calculated using data from S2 and S3) MDC ratios for coordination variability. The following couplings are reported: thigh flexion/extension – shank flexion – extension (o), shank internal/external rotation – foot inversion/eversion (◊), hip flexion/extension – knee flexion extension (□) and knee flexion/extension – ankle inversion/eversion(▽).

Table 5.7. Within day (calculated using data from S1 and S2) and between day (calculated using data from S2 and S3) MDC ratios for coordination variability. Thigh flexion/extension – shank flexion/extension (T_{FE}-S_{FE}), shank rotation – foot inversion/eversion (S_{IER}-F_{IE}), hip flexion/extension – knee flexion/extension (H_{FE}-K_{FE}), knee flexion/extension – ankle inversion/eversion (K_{FE}-A_{IE}).

	Within Day	Between Day
T_{FE}-S_{FE}	1.49	1.89
S_{IER}-F_{IE}	1.52	1.49
H_{FE}-K_{FE}	1.47	1.83
K_{FE}-A_{IE}	1.49	1.72

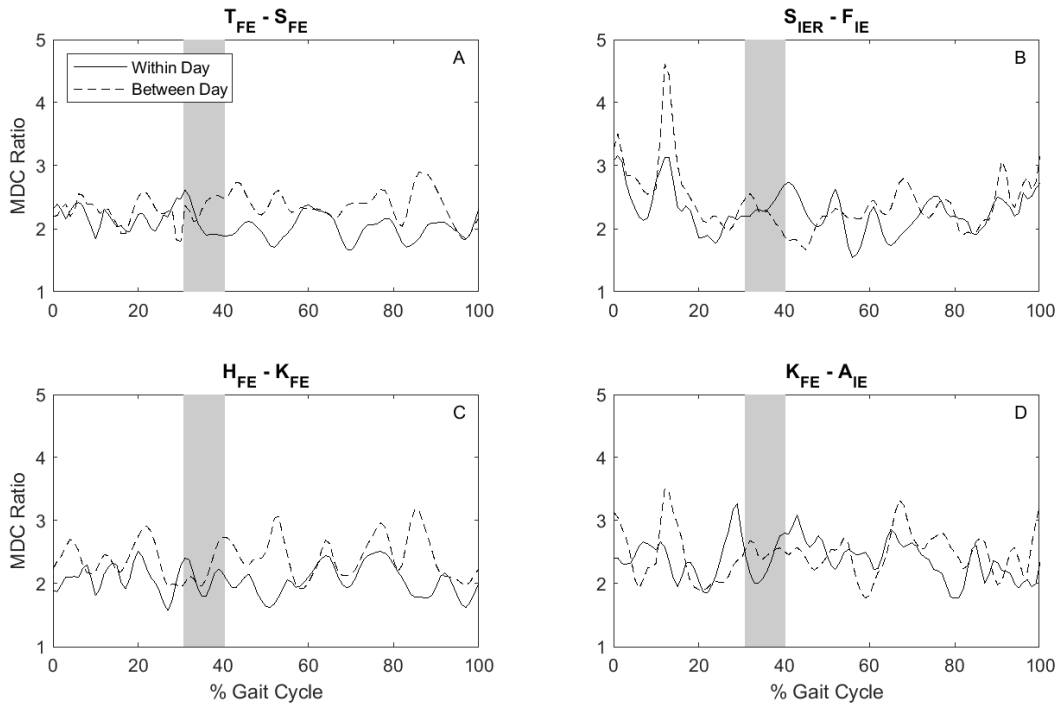


Figure 5.18. Within and between day Minimum Detectable Change (MDC) ratios in coordination variability across the gait cycle. The following couplings are reported: A) thigh flexion/extension – shank flexion/extension, B) shank internal/external rotation – foot inversion/eversion, C) hip flexion-extension – knee flexion extension and D) knee flexion/extension – ankle inversion/eversion. The MDC ratios for within day (calculated using data from S1 and S2) are shown with a solid line. The MDC ratios for between day (calculated using data from S2 and S3) are shown with a dashed line. The shaded area represents the range of percentages in the gait cycle that each participant transitioned from the stance to the swing phase ($\bar{\zeta}_{s,p}$, defined in Equation 5.3).

In the 1D coordination variability data, the within day MDC ratios had a mean and standard deviation (across the duration of the gait cycle) of: 2.07 ± 0.21, 2.28 ± 0.34, 2.06 ± 0.24, 2.38 ± 0.31 and the between day MDC ratios: 2.34 ± 0.23, 2.43 ±0.49, 2.40 ± 0.31, 2.47 ± 0.37 for thigh flexion/extension – shank flexion/extension, shank rotation – foot inversion/eversion, hip flexion/extension- knee flexion/extension, knee flexion/extension – ankle inversion/eversion respectively (Figure 5.18). The smallest MDCR recorded at any time point was 1.55 and the highest was 4.62.

An example application of the MDC to data collected within this study showed that absolute values calculated from the MDC ratios varied considerably both throughout the gait cycle and between participants (Table 5.8, Figure 5.19).

Table 5.8. The range of minimum detectable change values shown in Figure 5.19 as grey shaded areas above and below the data from session 1 (S1). The low example presents data from the participant with the smallest average hip flexion/extension – knee flexion/extension coordination variability at S1 and the high example presents data from the participant with the highest average coordination variability at S1. The smallest MDC boundaries represent the smallest range of the MDC about the data from S1 (at 28% of the gait cycle for both the low and high example where the MDC ratio was 2.00). The largest MDC boundaries represent the largest range observed about the MDC (at 95% of the gait cycle for the low and high example where the MDC Ratio was 1.97).

	Smallest MDC limits ($^{o2}\cdot s^{-2}$)		Largest MDC limits ($^{o2}\cdot s^{-2}$)	
	-	+	-	+
Low Example	590	1240	5590	11670
High Example	3170	6710	22890	47540

Kinematics

The mean joint angle time series ($\bar{J}$) had mean and standard deviations (across the duration of the gait cycle) of 4.5 ± 1.3º , 6.0 ± 0.6º, 5.6 ± 1.5º, 6.1 ± 0.5º for ankle dorsi/plantar flexion, ankle inversion/eversion, knee flexion/extension and hip flexion/extension respectively in the within day comparison (Figure 5.20). The between day MDCs averaged across the gait cycle ± SD for ankle dorsi/plantar flexion, ankle inversion/eversion, knee flexion/extension and hip flexion/extension were: 4.5 ± 1.0º, 4.6 ± 0.5º, 4.8 ± 1.2º, 5.3 ± 0.7º respectively (Figure 5.20). The between day MDC was therefore similar to the within day MDC for ankle dorsi/plantar-flexion (Figure 5.20A) but lower for the other three joint angles investigated (Figure 5.20 B to D). Knee flexion/extension had higher MDCs in the swing phase compared to the stance phase (Figure 5.20C). Ankle inversion/eversion and hip flexion/extension showed more consistent MDCs that did not vary by more than 2º in any particular phase of the gait cycle (Figure 5.20B&D).

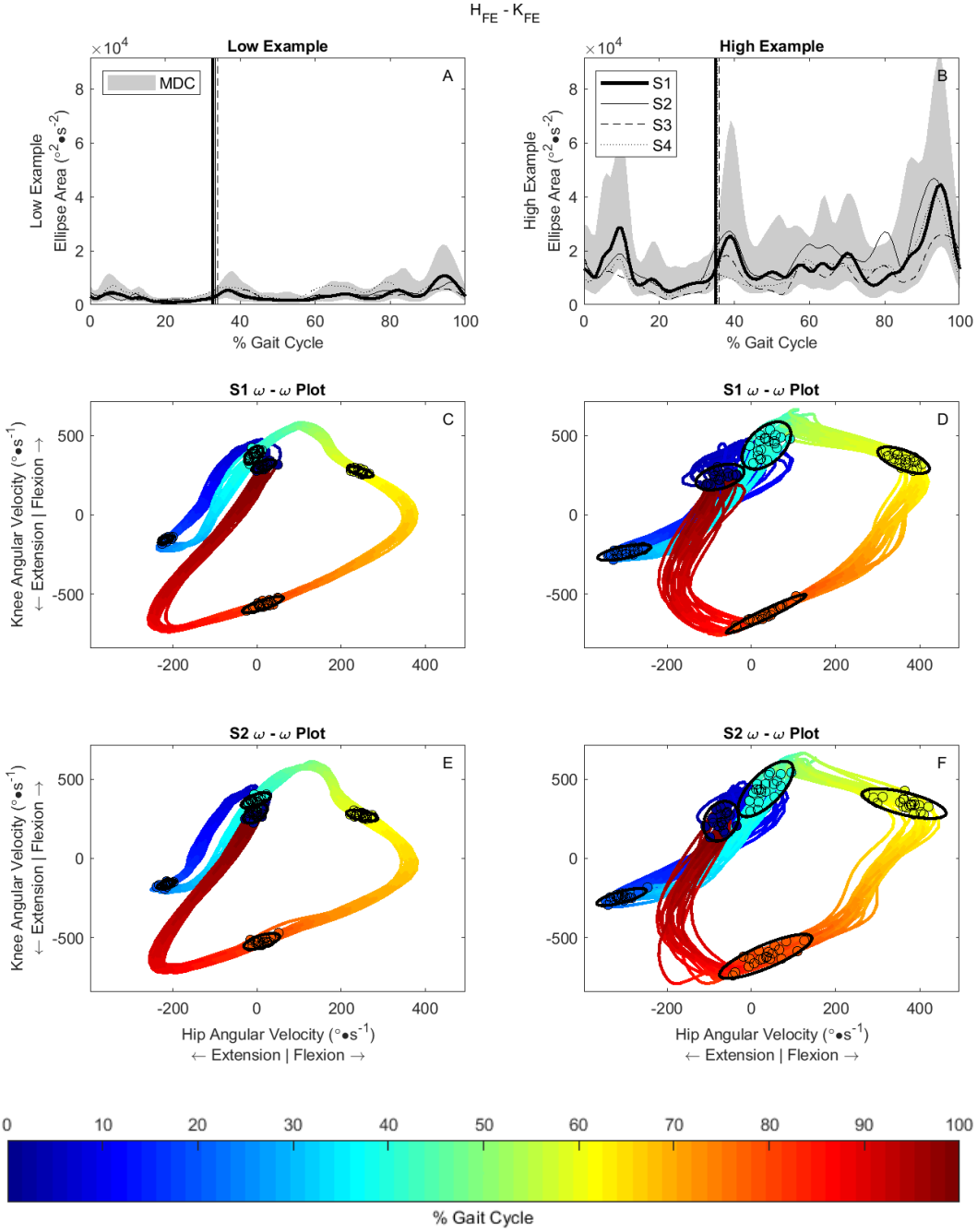


Figure 5.19. Example applications of the between day MDC ratio (calculated from the group) to the participant with the lowest (A) and highest B) average hip flexion/extension – knee flexion/extension coordination variability in Session 1 (S1). Data from each of the four sessions are plotted: S1±MDC (thick solid line with grey shaded area about it), Session 2 (S2, same day as S1, thin solid line), Session 3 (S3, +1 week, dashed line) and Session 4 (S4, +8 weeks, dotted line). Vertical lines represent the average percentage of the gait cycle that each participant transitioned from stance to swing at session where line style follows the same convention used for variability timeseries. Example angular velocity – angular velocity plots for the participants with the lowest (C) and highest (D) variability using data collected in S1. Example angular velocity – angular velocity plots for the participants with the lowest (E) and highest (F) variability using data collected in S2.

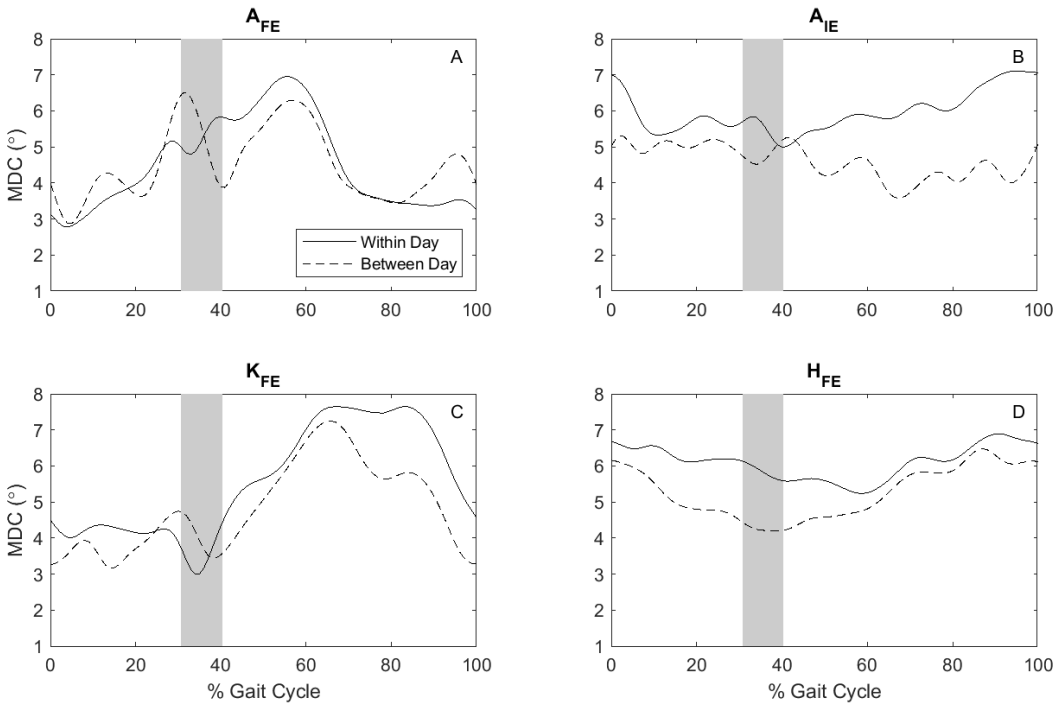


Figure 5.20. Minimal Detectable Change in joint angles across the gait cycle for within day (solid line) and between day (dashed line) comparisons. The following joint angles are reported: A) ankle dorsi/plantar flexion B) ankle inversion/eversion C) knee flexion/extension D) hip flexion/extension. The shaded vertical patch represents the range of times within the gait cycle that the participants transitioned from stance to swing phase.

5.3.5 Case study

Coordination variability averaged across the gait cycle

The case study participant reported two sources of pain when they returned to the lab for the fourth training session. The participant stated that they felt pain in their left heel which was rated as 4 when running during the testing session. They also reported that they felt pain in both calves which they described as delayed onset muscle soreness and rated at a severity of 2 (scale 1 to 5 where 5 is high and 1 is low pain).

The average coordination variability of the case study participant was frequently within or close to the 25-75th percentile of the data created from the other 19 participants. The data from S1 was often higher than the 75th percentile compared to the data from S2 and S3 (Figure 5.21) but was only greater than the 90th percentile at S1 for hip flexion/extension – knee flexion/extension.

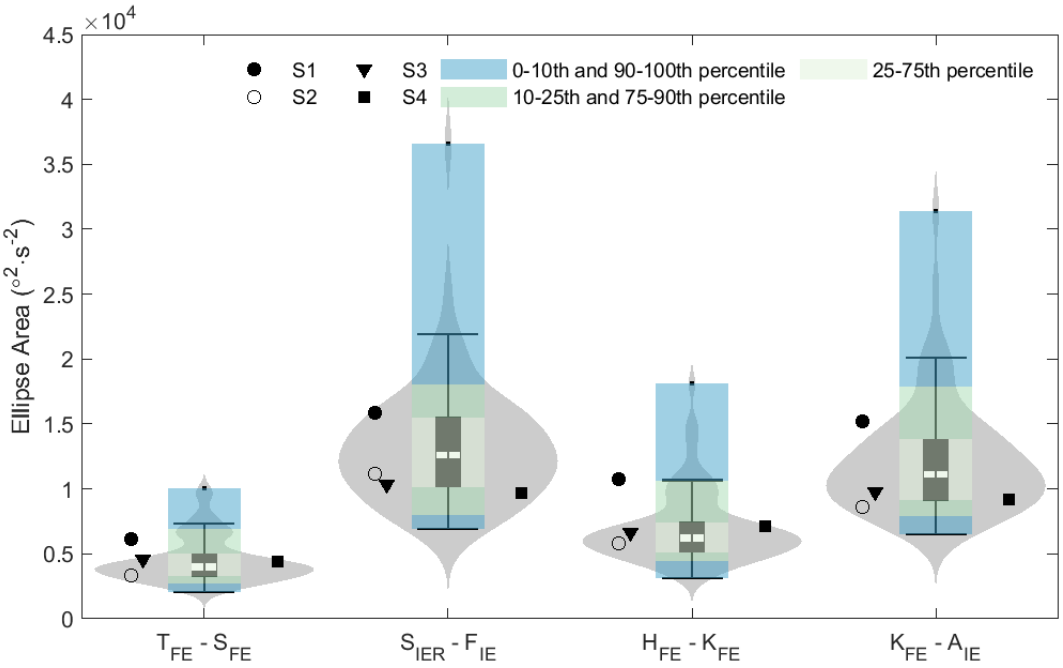


Figure 5.21. Average coordination variability across the gait cycle in the case study participant compared to the other 19 participants. Grey shaded violin plots demonstrate the distributions of average coordination variability across the gait cycle (created from 19 participants right legs from all four data collection sessions) for thigh flexion/extension – shank flexion/extension, shank rotation – foot inversion/eversion, hip flexion/extension – knee flexion/extension, knee flexion/extension – ankle inversion/eversion. The boxplots represent the same data but indicate the median, interquartile range, range and outliers. The coloured shaded area represents additional information about the percentile ranges of the violin plots data. The case study participant's left side average coordination variability is represented in black for Session 1 (filled circle), Session 2 (unfilled circle), session 3 (triangle) and session 4 (square).

No changes greater than the MDC were observed in average coordination variability between S1 and any of the other three sessions for thigh flexion/extension – shank flexion/extension and hip flexion/extension – knee flexion/extension. (Figure 5.22). A decrease in Shank rotation – Foot inversion/eversion variability that was greater than the MDC was observed at S3 and S4 (Figure 5.22) and at S2 for knee flexion/extension – ankle inversion/eversion. In all these instances, the measure recorded at S2, S3 and S4 were all more similar to one another than the measure taken at S1.

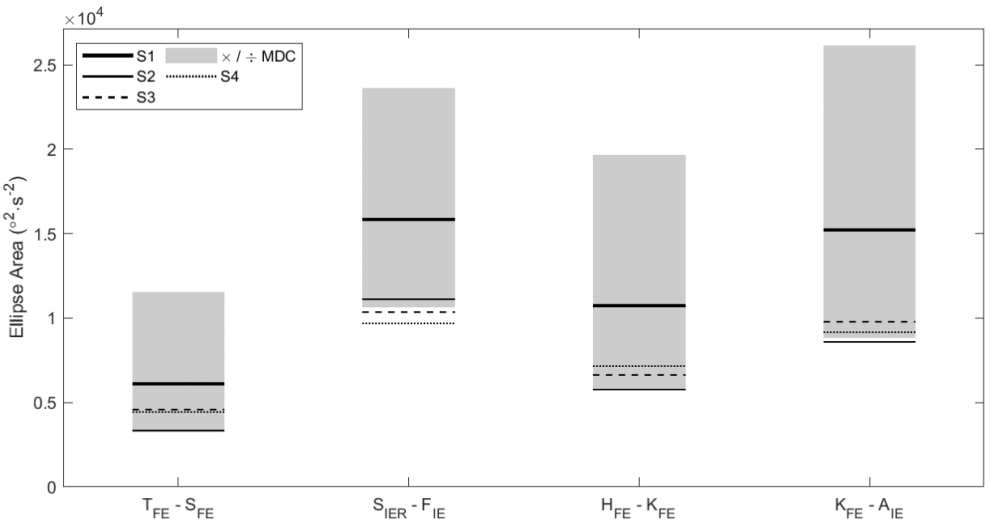


Figure 5.22. Comparison of average coordination variability across the gait cycle between sessions in the case study participant. Thigh flexion/extension – shank flexion/extension (T_{FE}-S_{FE}), shank rotation – foot inversion/eversion (S_{IER}-F_{IE}), hip flexion/extension – knee flexion/extension (H_{FE}-K_{FE}), knee flexion/extension – ankle inversion/eversion (K_{FE}-A_{IE}). Data from session 1 (S1) is plotted with a thick line and is surrounded by the MDC boundaries in grey shading. Session two (S2), three (S3) and four (S4) are plotted with a thin line, dashed line and dotted line respectively. Lines that are situated outside of the grey shaded areas represent changes greater than the MDC. Lines that are situated within the grey shaded areas represent that the difference between that line and session 1 was not greater than the minimum detectable change.

Coordination variability time series

When the average coordination variability of the case study participant's left leg was compared to the rest of the participant group, the variability at session 1 was in the top 10th percentile of coordination variability recorded for between 17 and 35% of the gait cycle duration (Figure 5.23, Table 5.9). Coordination variability from sessions 2, 3 and 4 was less frequently in the top 10th percentile (Table 5.9) and spent the majority of the gait cycle within the 25th to 75th percentile of the values recorded from the rest of the population (Figure 5.23). Coordination variability of the knee flexion/extension – ankle inversion/eversion coupling was in the bottom 10th percentile for 14, 7 and 13% of the gait cycle at sessions 2, 3 and 4 respectively (Table 5.10). This was mostly the result of periods of low variability relative to the comparison population at periods during the swing phase. There was one example where the case study participant's left leg had greater coordination variability than any of the comparison group (hip flexion/extension – knee flexion/extension, 26-33%, Figure 5.23C) and none where it was the lowest.

For the case study participant, there were a number of examples when the difference in variability between S1 (the first measurement) and S4 (when the participant experienced pain when running) exceeded the minimum detectable change (Figure 5.24 C,G&E). There were

however no instances where the difference between S2 (which occurred on the same day as S1) and S4 exceeded the minimum detectable change (Figure 5.24B,D,F&H).

Table 5.9. The percentage of the gait cycle that the coordination variability of the case study participant was greater than the 90th percentile of the comparison population in each data collection session. Thigh flexion/extension – shank flexion/extension (T_{FE}-S_{FE}), shank rotation – foot inversion/eversion (S_{IER}-F_{IE}), hip flexion/extension – knee flexion/extension (H_{FE}-K_{FE}), knee flexion/extension – ankle inversion/eversion (K_{FE}-A_{IE}).

	% duration of gait cycle in 90-100th percentile			
	Session 1	**Session 2**	**Session 3**	**Session 4**
T_{FE}-S_{FE}	20	0	0	4
S_{IER}-F_{IE}	17	0	4	0
H_{FE}-K_{FE}	35	5	1	7
K_{FE}-A_{IE}	23	0	0	0

Table 5.10. The percentage of the gait cycle that the coordination variability of the case study participant was lower than the 10th percentile of the comparison population in each data collection session. Thigh flexion/extension – shank flexion/extension (T_{FE}-S_{FE}), shank rotation – foot inversion/eversion (S_{IER}-F_{IE}), hip flexion/extension – knee flexion/extension (H_{FE}-K_{FE}), knee flexion/extension – ankle inversion/eversion (K_{FE}-A_{IE}).

	% duration of gait cycle in 0-10th percentile			
	Session 1	**Session 2**	**Session 3**	**Session 4**
T_{FE}-S_{FE}	0	1	0	0
S_{IER}-F_{IE}	0	6	4	6
H_{FE}-K_{FE}	0	0	8	0
K_{FE}-A_{IE}	0	14	7	13

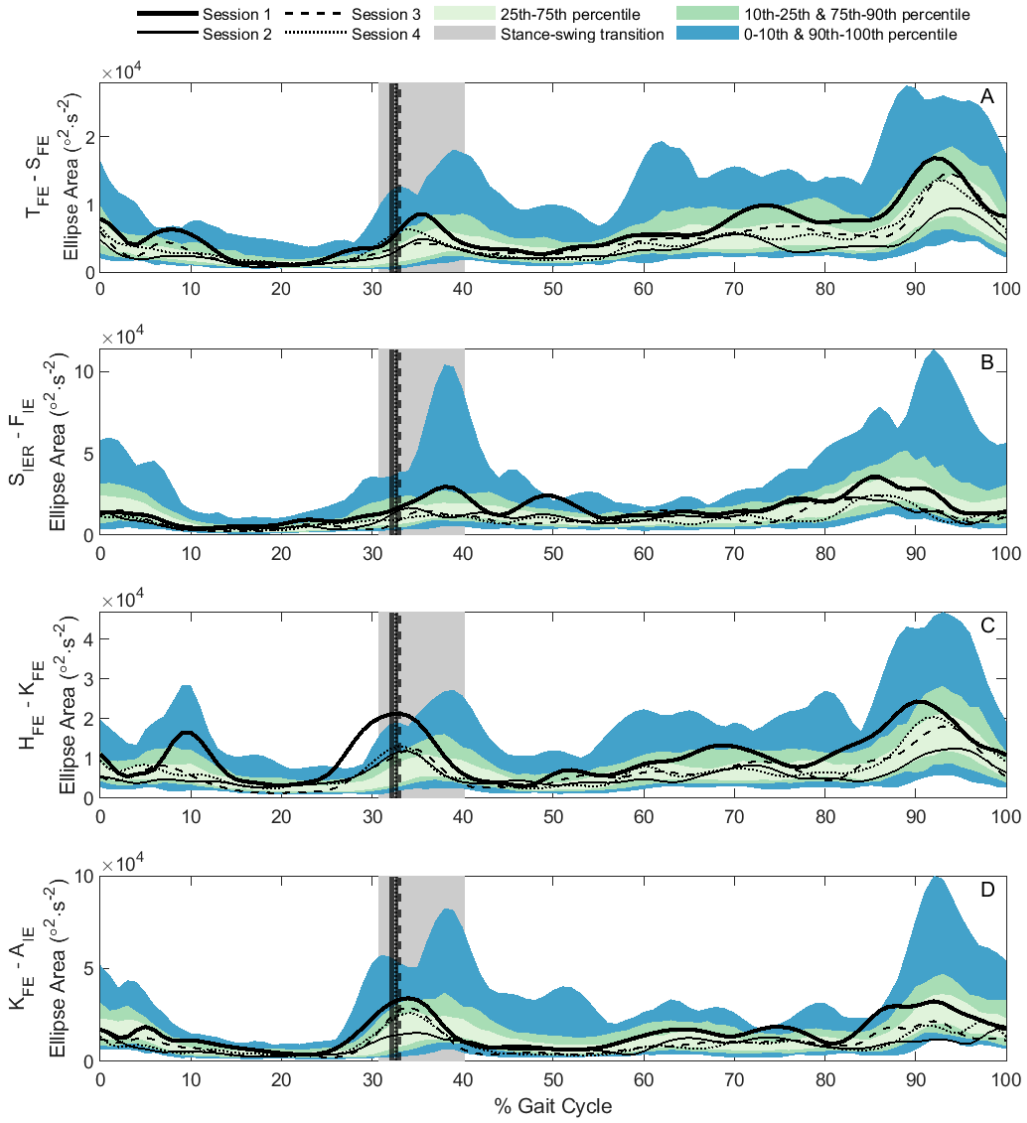


Figure 5.23. The case study participant's left side average coordination variability compared to the other 19 participants. The following couplings are reported: A) thigh flexion/extension – shank flexion/extension B) shank rotation – foot inversion/eversion C) hip flexion/extension – knee flexion/extension D) knee flexion/extension - ankle inversion/eversion. Session 1 (S1) is plotted with a thick line. Session two, three and four are plotted with a thin line, dashed line and dotted line respectively. The coloured patches represent data from the 19 other participants right legs: the pale green represents the central 50% of values recorded, the darker green represents the next 15% (i.e. 10th-25th and 75th-90th percentiles) and the blue sections represent the highest and lowest 10% of coordination variabilities recorded. Vertical lines represent the transition from stance to swing of the comparison group (grey shading) and for sessions one to four of the case study participant (thick, thin, dashed and dotted).

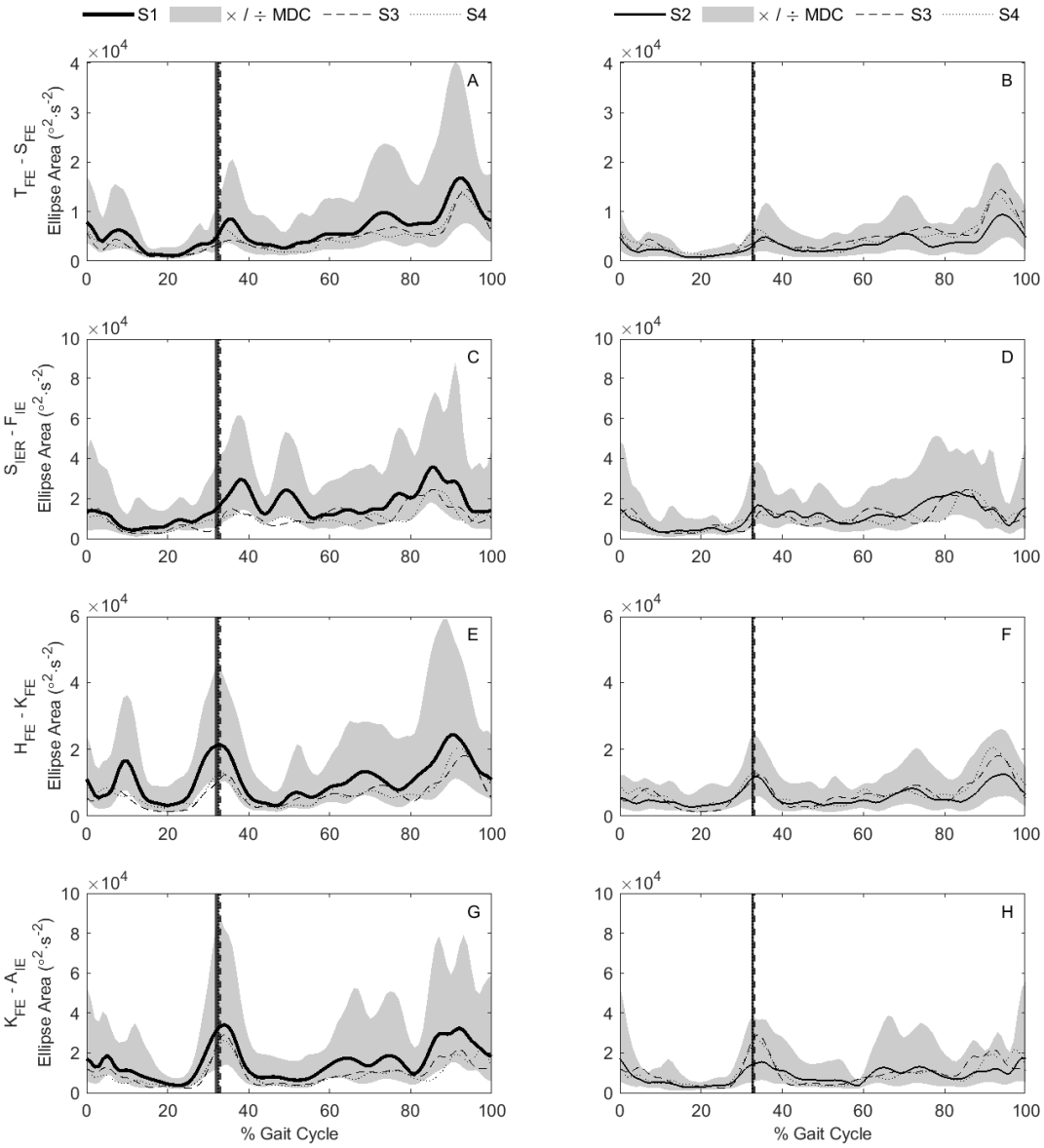


Figure 5.24. Comparison of using Session 1 or Session 2 as a baseline from which to detect change. Coordination variability for the case study participant at Session 1 (S1, thick solid black line) surrounded by the minimum detectable change boundaries (grey shaded area, left column of subplots) and at Session 2 (S2, thin solid black line) surrounded by the minimum detectable change boundaries (grey shaded area, right column of subplots) for thigh flexion/extension – shank flexion/extension, shank rotation – foot inversion/eversion, hip flexion/extension – knee flexion/extension and knee flexion/extension – ankle inversion/eversion. Sessions three (dashed line) and four (dotted line) are plotted on all axes. When these lines are situated within the grey shaded area the change from S1 (left) or S2 (right) to that session was less than the minimum detectable change. If the data line appears above or below the shaded area, the change that occurred between sessions was greater than the minimum detectable change. Vertical lines represent the average percentage of the gait cycle that the case study participant transitioned from stance to swing at each session and use the same formatting as for the data lines.

5.4 Discussion

This chapter has had two separate foci: the first to report the within and between day repeatability of the velocity ellipse method as a measure of coordination variability and the second to investigate a case study of longitudinal data in a participant who developed heel pain between testing sessions. In reporting the between and within day repeatability of the coordination variability measure, this chapter has reported the minimal detectable change (MDC) of the VEM when applied to four commonly used coordination couplings in running gait. MDC ratios were presented that showed the repeatability of coordination variability for each coupling both at each percentage of the gait cycle and as averages across the gait cycle. These values can be used in future research to support the interpretation of results in understanding whether intra-individual changes are of a meaningful magnitude, where it is not possible to attain repeated measurements from that individual. It was hypothesised that within day minimum detectable change would be less (i.e. more repeatable) than between day measures of coordination variability. This was true for some coordination variability measures, but in other instances the between day MDC was similar to or less than the within day measure.

The second focus of this study was to use the MDCs to interpret longitudinal changes in coordination variability and joint angles in a participant who began to experience pain in their left heel between the third and fourth testing sessions (1 week and 8 weeks after the first testing session respectively). It was hypothesised that the case study participant would have low coordination variability compared to the comparison group in the first three sessions. This would align with hypotheses that low coordination variability might result in the repetitive loading and chronic damage of biological tissue that might lead to reports of pain or injury (Hamill et al., 1999). In the fourth session an increase in the participants coordination variability was hypothesised, as the majority of cross sectional studies investigating coordination variability and injury have found higher coordination variability in the injured group compared to a healthy group (Baida et al., 2018). The data did not suggest convincing changes in coordination variability to have occurred within the participant from the first three sessions to the fourth, nor did the participant demonstrate coordination variability that was obviously high or low in comparison to the rest of the participant group at any of the testing sessions.

5.4.1 Repeatability

This is the first research into the repeatability of the VEM and therefore findings cannot be compared to previous research. However, the VEM is derived from kinematic gait data for which there have been numerous reliability investigations. The MDC in joint angles reported

in this research was comparable or reduced compared to the results of other reliability studies conducted in walking gait (Table 5.11) which supports that these findings would be relevant to other researchers in other labs using similar data collection methods.

Table 5.11. Comparison of MDC measurements from this and other research studies. The SEM (Standard Error of Measurement) of joint angles averaged across the gait cycle reported in other research was converted into MDCs by multiplying the SEM by [1.962 x √2]. The joint angles reported are: hip flexion/extension (H_{FE}), knee flexion/extension (K_{FE}), ankle dorsi/plantar flexion (A_{DP}), ankle inversion/eversion (A_{IE}).

Joint Angle	Schwartz, Trost and Wervey (2004) converted MDC (°)*	A. Bates, McGregor and Alexander (2016) converted MDC (°)	Average gait cycle MDC in this research (°)	
			Within-Day	Between Day
H_{FE}	6.9	6.4	6.1	5.3
K_{FE}	6.9	6.7	5.6	4.8
A_{DP}	5.5	5.9	4.5	4.5
A_{IE}	Not reported	11.3	6.0	4.6

***Values estimated from graph**

Errors in coordination variability were found to be greater when the magnitude of coordination variability was higher in both discrete and time-series metrics therefore it was deemed appropriate to transform the data prior to calculating MDC ratios so as not to violate statistical assumptions of heteroscedasticity. Atkinson and Nevill (1998) highlighted that heteroscedasticity is common in sport science data. Recognition of heteroscedasticity in coordination variability measured using the velocity ellipse method is an important consideration for the interpretation of these data. Researchers must consider that the absolute magnitude of change that could occur as the result of an intervention might be affected by the magnitude of the pre-intervention measure and the direction of change expected. For example, the MDC ratios could be very similar (2.00 at 28% and 1.97 at 95%) at different phases of the gait cycle but when translated into absolute values, the changes required to detect a meaningful change are very different (Figure 5.19, Table 5.8). In addition to this smaller changes are required to exceed the MDC if a decrease occurred compared to an increase (Figure 5.19, Table 5.8).

There is no prior research to compare repeatability of coordination variability using the velocity ellipse method with, nor are there published boundaries to define excellent, good, acceptable or poor MDC ratios. Overall, the MDC ratios for average coordination variability across the gait cycle were between 1.47 (within day hip flexion/extension – knee flexion/extension) and 1.89 (between day thigh flexion/extension – shank flexion extension). Consequently, in the most repeatable examples an increase of at least 47% and decrease of

approximately 32% would have to be observed to be classed as meaningful. Furthermore, in the least repeatable measure, coordination variability would have to increase by 89%, or decrease by approximately 47%. Even in the most repeatable case, these seem like large changes and may raise question as to how repeatable measures of coordination variability are. For the time series coordination variability data, the MDC values were higher again, with the lowest mean MDC ratio values of 2.06 and maximum of 2.43 (with a range of 1.55 to 4.62). To add further context, several repeatability metrics from other research studies have been reported in Table 5.12. Some of their interpretations are based upon 5 or 10 % CV boundaries, the use of which has received criticism for being arbitrary (Atkinson and Nevill, 1998) and others do not comment on whether their results indicate adequate repeatability or otherwise. Relative to the examples provided, the values in this research are high. The low repeatability observed may negatively impact the ability of the velocity ellipse measure to detect changes in a clinical setting and also has implications for research that aims to detect relationships between coordination variability and injury in that large sample sizes would be required to reach statistical power. Further information is required to ratify the usefulness of coordination

Table 5.12. Example comparison data from other measures in sport science of reported Coefficients of Variation (CoV). The geometric standard deviation (Equation 5.11) is comparable to the CoV when 1 is subtracted from its value (Bland and Altman, 1996b).

Reference	Coefficient of Variation * ≈ estimated from geometric standard deviation	Criteria for interpretation / interpretation
Bland and Altman (1996a)	≈ 49.6%	"rather too large for the approximation to be reliable"
Ball and Scurr (2010)	1 to 25%	British Association of Sport and Exercise Sciences typical error measurement CoV % <5% = acceptable
Mizuguchi et al. (2015)	1 to 22% for 90% CoV	CoV < 10%
Hunter, Marshall and McNair (2004)	0 to 10 %	No comment made
Williams, Bradshaw and Maschette (2007)	8%	No comment made
$\overline{\boldsymbol{V}}$ **in this chapter**	≈ 15 to 26%	
$\boldsymbol{V}$ **in this chapter**	≈ 17 to 74%	

variability as measures with low repeatability can still differentiate between individuals if the range of values measured in a group is very diverse (Bland and Altman, 1996a).

Whilst the primary aim was to determine the repeatability of coordination variability measures there are several other observations that can be made from the MDC data presented that are worthy of comment. The MDC ratios calculated for the discrete measures were much lower (range 1.47 to 1.89, Figure 5.17) than those calculated for the coordination variability time series (average MDC ratios ranged from 2.06 to 2.43, Figure 5.18). This can be explained by considering that any between session (S1, S2 and S3) fluctuations that occurred must apply across an entire movement phase to affect the average value by the same amount that they affect each pointwise calculation. Furthermore, if, for example, coordination variability were higher in S1 than S2 for the first 50% of gait and then lower for the final 50% the higher coordination variability in the first half of the movement could offset the decrease observed in the second half. This is another means by which the average coordination variability measure is likely to appear more repeatable than the time series comparison.

When comparing the repeatability of coordination variability metrics (both discrete and time series measures) within day measurements were generally more repeatable compared to those taken between days (i.e. the MDC log ratio was higher for between day, Figure 5.17 & Figure 5.18). This is consistent with the expectation that changes that occurred within day may have a higher total contribution from variations in marker placement between sessions whereas between day measurements may contain similar methodological error, but also have increased biological variation due to greater variation in technique having been observed between days than on the same day. Whilst this was true for most of the coordination variability measurements, a lower between day than within day MDC log ratio was observed for average shank internal/external rotation – foot inversion /eversion across the gait cycle (Figure 5.17B) and for short periods in some of the time series measures (e.g. shank internal/external rotation – foot inversion eversion at ~40% of the gait cycle). This finding seems unusual, but the same pattern was observed for the joint angle data in that the between day comparisons were more repeatable (Table 5.11). One possible reason for this observation could be if a familiarisation effect occurred from session 1 to session 2, thus artificially increasing the within day repeatability. Other research has reported that consistent spatiotemporal, kinematic and kinetic parameters can be measured after 8 minutes of continuous locomotion in inexperienced treadmill runners (Arnold, 2019). Before any data was collected for each session in this chapter, the participants had already spent 9 minutes running on the treadmill, albeit with a short interlude after the first 5 minutes to check all markers were firmly attached. An indication of their treadmill experience was not collected but anecdotally, all participants appeared comfortable with running on the treadmill from the first session therefore it seems

unlikely that familiarisation might have artificially inflated the within day repeatability. Another conceivable cause is that biological variation can be detected between sessions which are separated by as little as 10 minutes (Horst, Mildner and Schollhorn, 2017). It is possible that the biological variation that occurred between the within day sessions could be just as great or greater than that measured between days for some participants for certain measures, which might explain why the between day MDC was lower or similar to the within day MDC for some but not all measures.

5.4.2 Case Study

The MDC values were then used in the interpretation of data from a case study where a change in coordination variability could have been expected based upon the theories which link coordination variability and injury. One participant returned two months after their first data collection session reporting pain in their left heel when they ran. Although the source of the pain had not been medically diagnosed, when the pain was reported it was not associated with an acute injury event, therefore was likely to represent an overuse injury or transient inflammation. Previously, overuse injuries have been associated with lower coordination variability from a theoretical standpoint (Hamill et al., 1999; Hamill, Palmer and van Emmerik, 2012) and in some cross-sectional studies (Heiderscheit, Hamill and van Emmerik, 2002) but it has been highlighted that we cannot be sure if the lower coordination variability occurred as a result of the injury or may have either caused or been a contributing factor to the injury (Hamill, Palmer and van Emmerik, 2012). Other evidence has found coordination variability to be increased in injured populations (e.g. Baida et al., 2018; Desai and Gruber, 2020), and links have also been made questioning whether higher variability may contribute to the injury risk (Hamill, Palmer and van Emmerik, 2012) on the basis of it being a potential indicator of poor movement control (Baida et al., 2018). Furthermore, pain itself has been proposed as a potential factor that may result in a decrease in coordination variability (Hodges and Tucker, 2011). However, a research study specifically investigated within participant changes in coordination variability over the course of a run in participants with ilio-tibial band syndrome (Hafer and Boyer, 2017). They found no differences in coordination variability in a group whose pain increased over the course of the run compared to a healthy group and injured group with no pain.

It was hypothesised that the case study participant would have low variability in comparison to the rest of the population at S1, S2 and S3 based on the theory that low variability might have contributed to causing the injury or pain that they experienced when running 8 weeks on from their first testing session. Compared to the rest of the population, the average coordination variability measured for case study participant's left leg was never ranked as one

of the highest or lowest within the population and was often in the central 50% of the group. This suggested that the coordination variability of the case study participant was not different to comparison group and therefore did not support the hypothesis that the case study participant had low coordination variability compared to the other participants. The coordination variability time series data mostly supported these results as the case study participant largely remained in the central 50 percentiles of the comparison population, but there were some observations of note. Coordination variability was often greater than the 90th percentile of the comparison group at S1, but this was infrequent for the data collected at S2, S3 (Figure 5.23, Table 5.9). Coordination variability at S2, S3 for the case study participant were more similar to each other which may suggest caution in using data from S1, where coordination variability was frequently much higher, to be representative of the case study participant's coordination variability. There is no clear reason that can be taken from the data to explain why this is, but it is possible this is a result of an individual familiarisation response to the data collection process. At S1, coordination variability was higher than any other participant from 26 to 33 percent in the hip flexion/extension – knee flexion/extension coupling around the transition from stance to swing. At S2, S3 and S4 it was also high relative to the rest of the population (Figure 5.23) suggesting an area of potential interest. Furthermore, in sessions 2, 3 and 4 there were periods when coordination variability was low compared to the comparison population. Whilst interesting to note, these periods mostly occurred during the swing phase which, due to its unloaded nature, may be less relevant to the heel discomfort experienced by the case study participant. Thus, in this case study there was no strong evidence to support theories relating low variability to the onset of pain or injury and the hypothesis that they would have low variability compared to the group was rejected. Generally, the coordination variability of the case study participant was comparable to that measured in the rest of the participant group although a period of high variability in hip flexion/extension – knee flexion/extension around the stance-swing transition could be of interest. It is possible that high variability in the sagittal plane when the participant is pushing off from the ground with their forefoot may place unpredictable loads on the Achilles tendon which inserts at the calcaneus (heel), but this suggestion is speculative and would require further support from biomechanical modelling research.

The results from this case study also provided no clear evidence to support that the individual's coordination variability changed within the eight-week testing period either as a result of the potential overuse injury causing the pain, or the pain the participant was experiencing. Although a number of changes that exceeded the MDC values were detected between session one and session four (average shank rotation – foot inversion/eversion on the left leg, Figure 5.22 and multiple times for the time series, Figure 5.24A,C,E & G) when session four was

compared to session two using the same methods, no differences were detected at any time point across all of the couplings (Figure 5.24B,D,F & H). Session two took place on the same day as session one therefore we would not expect any clinically relevant change to have occurred between session one and session two, shedding doubt on the suggestion that a meaningful decrease in coordination variability was observed. Thus, the hypothesis that increased variability would be observed in the case study participant at session four compared to sessions one, two and three was rejected.

5.4.3 Limitations

When used on a single discrete statistical comparison the MDC should be interpreted as being a range which any future data point that is not meaningfully different, has a 5% chance of exceeding. Thus, the user could expect one false positive in every twenty comparisons. When the same principles are extended to the time series coordination variability metrics, the MDC was calculated for each percentage of the gait cycle to be an independent data point which was not related to the time point directly before or after it. The implications of a statistical method designed for discrete measures being applied to a time series is that the probability of detecting a change that exceeds the MDC at some point in the gait cycle in a participant is further increased. The likelihood may even be higher for non-smooth signals such as coordination variability for the same reasons outlined for statistical parametric mapping (Pataky, Robinson and Vanrenterghem, 2013). In the absence of methods which account both for interrelated time points and signal smoothness that are easily implementable and understandable, it was particularly valuable to have multiple records of baseline running gait data. This provided a means of scrutinising what may or may not have been a meaningful change and this would be recommended to anyone looking to measure changes in gait kinematics time series measures where only one time series is collected per session, such as with coordination variability. In the case study data, differences in coordination variability were observed when comparing the first testing session to the eight-week follow-up (S4). These differences were not present when the second testing session, which took place within just a few hours of the first, was used as the baseline value. The fact that such large changes can occur within the space of a few hours, when it is reasonable to assume nothing clinically relevant had changed within the participant, indicates that practitioners and researchers must be careful when interpreting changes in coordination variability and further emphasises the benefits of multiple data collections on the same individual.

In relation to the case study investigation, the case study participant reported significant pain in her left heel during running but the nature of the cause of this pain was not verified by a medical professional as being an injury. Nonetheless, the participant was in pain, a condition

that previous investigations have found to be a potential modifying factor relevant in changes to coordination variability (Cunningham et al., 2014; Bonacci et al., 2020). Despite this, no meaningful changes in coordination variability were observed suggesting that the coordination variability measure used here was not sensitive to this change in the same way that other coordination variability measures (namely continuous relative phase) have been shown to be sensitive to detecting participant with the early signs of Parkinson's disease (van Emmerik et al., 1999).

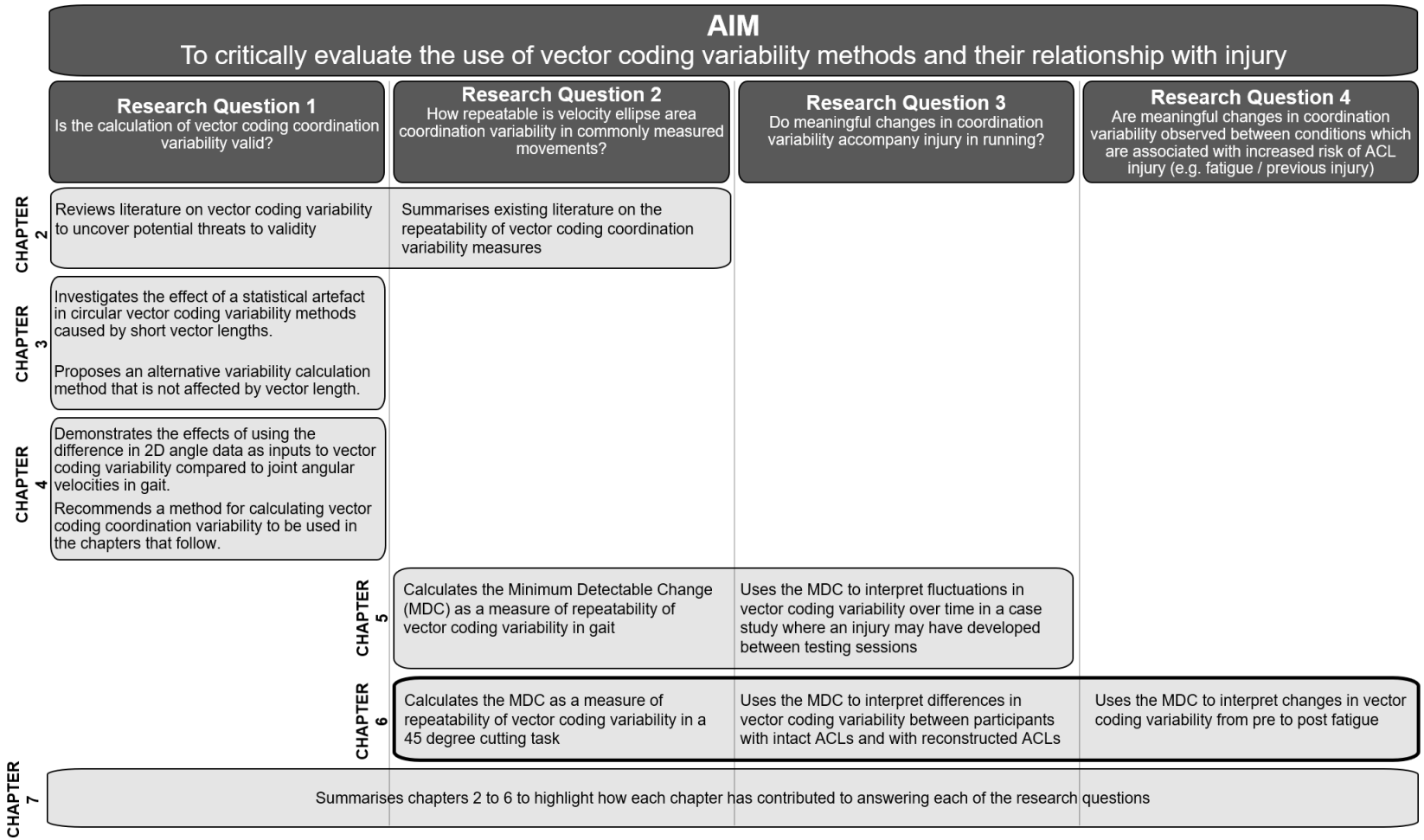
Finally, the use of case studies to understand the possible relevance of coordination variability in gait is not a strong source of evidence. However, many studies have studied cross-sectional differences in these measures and have not consistently found differences between groups. Thus, authors have highlighted the need to understand how these variables change over time within an individual more fully. This research is a first step towards this, though the initial results warrant caution in the use of the velocity ellipse method to detect changes in coordination variability in gait. It is possible that the methods (both specific to coordination variability and for the statistical analysis of the repeatability of 1D data), in place to assess coordination variability require further development. Further research is still required to determine whether coordination variability metrics provide clinically relevant information for lower limb overuse injuries.

5.5 Conclusion

This chapter has detailed the within day and between day repeatability of coordination variability measured using the Velocity Ellipse Method for discrete (average coordination variability across the gait cycle) and time series of four coordination variability couplings in running gait. Repeated measures of coordination variability data were found to be heteroscedastic in that the greater the variability measured, the larger the difference observed between repeated sessions, necessitating a log transform of the data for further statistical comparison. The minimum detectable change (MDC) measure was used as a metric of repeatability and was presented as a ratio due to the heteroscedasticity of the coordination variability data. Despite providing a best case scenario for repeat marker placement, and demonstrating that the repeatability of joint angles in this research was comparable with that published by other research groups, both within and between day MDC ratios were large compared to ratios reported for other measures in sport science. These findings indicated that coordination variability measures calculated using the velocity ellipse method may have low repeatability. The implications of this are that clinicians and practitioners may be unable to detect methodologically meaningful differences in coordination variability in individuals, which will also impact the ability to test whether clinically meaningful differences exist.

In addition to providing other users of coordination variability with knowledge of its repeatability, this chapter also developed understanding of how variability might be related to injury using a case study example of longitudinal data. In this example the case-study participant had transitioned from feeling no pain to feeling a high level of pain in their left heel in the eight-week testing period. The data from multiple testing sessions combined with the MDC suggested that no meaningful change in variability had occurred, yet information from the MDC and first testing session in isolation suggested otherwise. This highlighted the importance of collecting multiple trials where possible and emphasised how low repeatability of coordination variability may negatively impact its ability to provide useful information. Compared to the rest of the cohort, the case study participant was neither the most nor least variable. Their ranking within the group was inconsistent and did not obviously support that they had especially low or high coordination variability that might have been a contributing factor to the reported heel pain. This case study example therefore did not provide supportive evidence for theories linking coordination variability and injury or pain either cross sectionally or longitudinally.

Gait has been the most commonly investigated movement for studying coordination variability and injury to date due to the incidences of chronic injuries in runners but another injury type that has been linked to the repetitive loading – injury example is anterior cruciate ligament rupture (Wojtys, Beaulieu and Ashton-Miller, 2016). This injury is often considered as an acute injury, but some authors have suggested that the probability of sustaining an injury can be increased as a result of repetitive loading overtime that weakens the ligament and thus reduces the threshold at which it ruptures. This theory has similarities with the repetitive loading – injury hypothesis in the variability literature and some authors have therefore chosen vector coding coordination variability measures to investigate coordination variability in a different movement, namely the cutting manoeuvre. The next chapter therefore investigated the repeatability of coordination variability in cutting using the same methods demonstrated in this chapter to calculate the minimum detectable change. The minimum detectable changes were then used to support the interpretation of how fatigue affected coordination variability in cutting in a separate group of participants and the differences between participants with ACL reconstructions and a control group were compared.


AIM
To critically evaluate the use of vector coding variability methods and their relationship with injury
Research Question 1
Is the calculation of vector coding coordination variability valid?
Research Question 2
How repeatable is velocity ellipse area coordination variability in commonly measured movements?
Research Question 3
Do meaningful changes in coordination variability accompany injury in running?
Research Question 4
Are meaningful changes in coordination variability observed between conditions which are associated with increased risk of ACL injury (e.g. fatigue / previous injury)
CHAPTER 2
Reviews literature on vector coding variability to uncover potential threats to validity
Summarises existing literature on the repeatability of vector coding coordination variability measures
CHAPTER 3
Investigates the effect of a statistical artefact in circular vector coding variability methods caused by short vector lengths.
Proposes an alternative variability calculation method that is not affected by vector length.
CHAPTER 4
Demonstrates the effects of using the difference in 2D angle data as inputs to vector coding variability compared to joint angular velocities in gait.
Recommends a method for calculating vector coding coordination variability to be used in the chapters that follow.
CHAPTER 5
Calculates the Minimum Detectable Change (MDC) as a measure of repeatability of vector coding variability in gait
Uses the MDC to interpret fluctuations in vector coding variability over time in a case study where an injury may have developed between testing sessions
CHAPTER 6
Calculates the MDC as a measure of repeatability of vector coding variability in a 45 degree cutting task
Uses the MDC to interpret differences in vector coding variability between participants with intact ACLs and with reconstructed ACLs
Uses the MDC to interpret changes in vector coding variability from pre to post fatigue
CHAPTER 7
Summarises chapters 2 to 6 to highlight how each chapter has contributed to answering each of the research questions

CHAPTER 6: THE REPEATABILITY AND EFFECT OF FATIGUE AND ACL INJURY ON COORDINATION VARIABILITY IN A CUTTING MOVEMENT

6.1 Introduction

The anterior cruciate ligament is situated within the knee joint (Duthon, 2006) and functions to resist anterior translations of the tibia relative to the femur (Sakane et al., 1997) and knee rotational loads (Matsumoto et al., 2001). One reason why research into ACL injury has been relatively popular as a theme in sport science research is because many incidences are considered a 'non-contact' injury in that they occur without direct contact of an external force to the area of injury (Olsen et al., 2004). Many researchers have suggested that non-contact injury incidences can be reduced by implementing targeted interventions based on our understanding of ACL injury risk factors, some of which are biomechanical in nature (Hewett et al., 2015; Anderson et al., 2016). In this vein, there has been much debate around possible injury mechanisms. The majority of possible mechanisms through which the ACL is loaded and can be overloaded (injured) are based on the interactions of multiple joints and segments (Shimokochi and Shultz, 2008; Quatman, Quatman-Yates and Hewett, 2010). For example: concurrent hip extension and knee flexion have been suggested as potentially dangerous for the ACL upon impact with the ground (Hashemi et al., 2011), hip and knee internal rotation and knee valgus observed in videos of ACL rupture suggest medial limb collapse is an important factor in ACL injury (Olsen et al., 2004) and combined internal and valgus torque at the knee has been suggested to load the ACL in cadaver studies (Quatman, 2014).

Vector coding provides a means of analysing such interactions between joints and segments. Variability in the coordination of those interactions during cutting movements has been said to reflect an adaptive, flexible system (Weir et al., 2019). There is also evidence to suggest that ACL injury may not just be the result of a one-off supra-maximal load, but that low cycle material fatigue may cause damage to accumulate in the ligament that may also lead to injury (Wojtys, Beaulieu and Ashton-Miller, 2016). This theory is closely aligned with the variability – injury hypothesis, whereby low variability leads to repetitive loading of biological structures and the build-up of micro-damage. For these reasons, the variability of angle – angle plots of cutting movements has been investigated in peer-reviewed articles on four occasions (Pollard et al., 2005; Pollard et al., 2015; Samaan et al., 2015a; Weir et al., 2019) and has also been the subject of at least one doctoral thesis (Breen, 2012).

The same challenges hold true for coordination variability in cutting as are present in gait. The theories that suggest variability and injury could be related hypothesise that when variability is comparatively high or low an individual may be at increased risk of injury or re-injury of the ACL (Hamill et al., 1999; Hamill, Palmer and van Emmerik, 2012). One of the biggest challenges in this regard is defining where the thresholds for variability that is too high or too low might lie, and whether these boundaries are specific to individuals or not. As things stand, there are no guidelines available and so a result in either direction that has reached statistical significance is interpreted as relevant and important to injury risk.

To date, there is no published research that details the repeatability of coordination variability of joint couplings in cutting. Thus, it is very challenging to interpret what magnitude of change in a group of individuals or difference between groups of individuals in coordination variability might represent real change and therefore be relevant for better understanding ACL injuries. The lack of knowledge on the repeatability of coordination variability in cutting also means that research cannot be planned in a way to ensure the sample size is large enough to give the research sufficient power.

In the research articles that have measured coordination variability using vector coding in cutting, some authors have questioned whether coordination variability is higher or lower between groups which are known to have different incidences of ACL injury. For example, females are believed to be two to three times more likely to sustain an ACL injury than males (Prodromos et al., 2007; Montalvo, 2019), and people with a history of ACL injury are more likely to suffer a second ACL injury (Brophy, 2012; Wiggins et al., 2016; Grassi, 2020). Others have looked to measure how coordination variability is different under conditions where ACL injury risk is believed to be higher. For example, knee mechanics that are associated with increased risk of injury are more prevalent in unanticipated than anticipated cutting movements (Almonroeder, Garcia and Kurt, 2015). Fatigue has also been identified as an important factor to consider in rehabilitation when returning to sport following ACL reconstruction (Herrington, Myer and Horsley, 2013) and a number of research studies have identified a shift towards movement patterns that are associated with ACL injury in a fatigued state (e.g. Borotikar et al., 2008; McLean and Samorezov, 2009; Thomas et al., 2015) leading these authors to suggest that fatigue is an important factor to consider for ACL research.

Pollard et al. (2005) were the first to measure the variability of an angle – angle coordination plot during an unanticipated cutting movement investigating differences in coordination variability between females and males. They found that knee flexion/extension – knee rotation and knee flexion/extension – hip rotation was lower in females compared to males (F: 6.6°, M: 12.4° and F:7.7°, M:13.9° respectively) when averaged over the first 40% of the stance

phase of the cut (Pollard et al., 2005). This lower variability was hypothesised to demonstrate a less adaptable coordination pattern, that when challenged by environmental perturbations might be more susceptible to knee ligament injury. The same lead author then also went on to investigate coordination variability in females who had undergone Anterior Cruciate Ligament (ACL) reconstructions (Pollard et al., 2015). Individuals with a surgical reconstruction of their anterior cruciate ligament demonstrated increased coordination variability for hip rotation knee ab/adduction (ACLR: 27.2 ± 11.5°, CNTL: 19.7 ± 6.8°, $p = 0.04$), hip flexion/extension – knee ab/adduction (ACLR: 26.0 ± 13.3°, CNTL: 18.6 ± 5.3°, $p = 0.05$), knee ab/adduction – knee flexion/extension (ACLR: 13.5 ± 5.7°, CNTL: 2.7 ± 6.8°, $p < 0.01$), and knee ab/adduction – knee rotation (ACLR: 26.4 ± 10.8°, CNTL: 19.3 ± 4.5°, $p = 0.03$), compared to females who had not had ACL injuries in the first 40% of the stance phase of the cut (Pollard et al., 2015). This finding was contrary to the authors' predictions, but it was suggested that the higher variability might compromise the control of joint movement when the conditions of the movement were demanding (and therefore also be associated with increased risk for ACL injury).

Two further studies have investigated within participant changes in coordination variability either due to fatigue (Samaan et al., 2015a) or anticipation (Weir et al., 2019). When the hamstrings were fatigued in isolation, decreases in hip internal/external rotation – knee internal/external rotation variability were observed for the impact phase (pre fatigue 0.417 ± 0.154, post fatigue 0.344 ± 0.111, $p = 0.015$) and weight acceptance phases (pre fatigue 0.526 ± 0.098, post fatigue 0.453 ± 0.137, $p = 0.043$, both phases together represent approximately 0-30% of the stance phase) and in hip ab/adduction – knee internal external rotation variability during the weight acceptance phase (pre fatigue 0.531 ± 0.123, post fatigue 0.446 ± 0.121, p = 0.038, approximately 18-30% of the stance phase of the cut, Samaan et al., 2015a). This decreased variability was interpreted as representing fewer movement solutions available to the participant due to fatigue in their hamstring muscle group. It was suggested that the repeated use of this reduced number of movement patterns might be a possible cause of increased micro-trauma to the ACL that could lead to injury. When comparing anticipated and unanticipated cuts in a group of males, Weir et al. (2019) observed higher coordination variability for hip flexion/extension – knee flexion/extension (from 0-2% of the stance phase of the cut) and hip rotation – knee flexion/extension (from 0-4% of the stance phase of the cut) in unanticipated compared to anticipated cutting manoeuvres. The authors suggested the higher variability could have been observed in unanticipated cutting compared to anticipated cutting because the task is more complex and required the athletes to utilise more degrees of freedom and suggest that this increased variability may be a positive feature for performance (to evade opponents) and injury (to distribute joint loading).

To summarise, the four published articles investigated factors which are commonly associated with an increased risk of ACL injury and saw contrasting outcomes in how coordination variability differed between those factors. Being female (Pollard et al., 2005) or having isolated hamstring fatigue were associated with lower coordination variability (Samaan et al., 2015a). In comparison, having had an ACL reconstruction (Pollard et al., 2015), or performing an unanticipated (as opposed to anticipated) change of direction task was associated with higher coordination variability (Weir et al., 2019). Further research investigating these questions would be beneficial to understand if the same findings can be repeated and to support the conclusions and the implications for ACL injury. This is particularly relevant considering the limitations of vector coding analyses based on circular statistics that were highlighted in Chapter 3. It would be interesting to understand if the same results are observed when coordination variability is calculated using methods that are not affected by the vector length artefact and when the angular dynamics are derived from angular velocities (compared to the traditional change in angle techniques).

The first aim of this chapter was therefore to understand the within-day repeatability of the Velocity Ellipse Method for measuring coordination variability in a cutting movement in four coordination couplings that have been used in published literature: hip flexion/extension – knee flexion/extension, hip internal/external rotation – knee flexion/extension, hip internal/external rotation – knee internal/external rotation and knee flexion/extension – knee ab/adduction. This would be performed on a group of healthy individuals and provide reference values to support the interpretation of other data collected within this chapter.

The second aim was to compare the effect of fatigue on two participant populations (one with Anterior Cruciate Ligament reconstructions (ACLR) and the other whose ACL ligaments were intact (ACLI)). It was hypothesised that 1) coordination variability would be greater in the ACLR group compared to ACLI as this has previously been observed by Pollard et al. (2015) 2) that fatigue would result in a decrease in coordination variability (as had been observed by Samaan et al. (2015a)) and 3) that the decrease observed in the ACLR group would be greater than that observed in the ACLI group.

6.2 Methods

6.2.1 Study design

Two separate data collections took place with two different participant groups. One data collection session was devised to investigate the repeatability of coordination variability in a change of direction movement in healthy female team sports players (repeatability study). The other data collection was used to understand the effect of fatiguing exercise on coordination

variability in female ACLR and ACLI populations (fatigue study). Both data collections employed a repeated-measures design where participants were asked to perform multiple repetitions of two different movement tests on each leg before and after an intervention of rest (repeatability study) or fatiguing exercise (fatigue study) (Figure 6.1). Markers remained in place between testing sessions so that errors in repeat marker placement would not contribute to the changes observed between sessions.

6.2.2 Participants

Repeatability Study

Ten females were recruited to attend one testing session in the University of Bath's Applied Biomechanics Lab (Table 6.1). Inclusion criteria required that participants were female team sports players participating in their sport without restriction due to injury at the time of testing.

Fatigue Study

Two groups of participants were recruited. The first group (ACLR) consisted of females who had all sustained an ACL rupture, had an ACL reconstruction and had been cleared by medical personnel to have made a return to their sport since their operation. The second group included participants with intact ACL ligaments (ACLI) and required participants to have not previously suffered a major lower limb injury (such as fractures, ligament ruptures or injuries requiring surgery). All participants were female team sports players who were participating in their sport without restriction at the time of testing and the characteristics of each group are presented in Table 6.1.

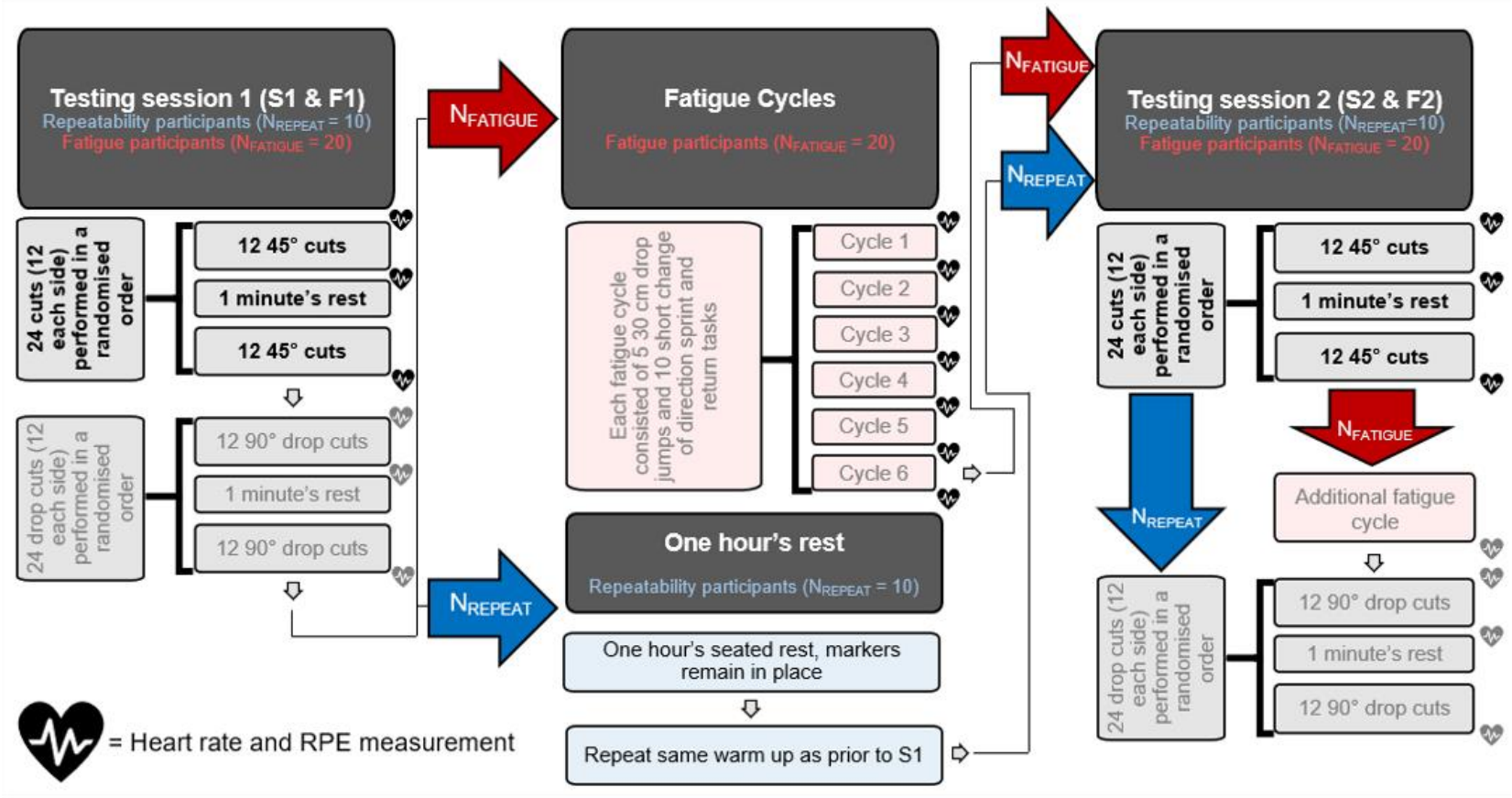


Figure 6.1. Schematic overview of data collection for repeatability and fatigue data collections. The dark grey boxes outline different sections within the data collection protocol. Lighter shaded boxes situated below each dark grey box provide further detail of the components comprising each section. The distinction between components that were only completed in the repeatability study or only completed in the fatigue study have been highlighted in blue and red shading respectively. The data collection protocol involved many components, not all of which are the focus of this chapter or for use in this thesis. Those components that have not been analysed in this chapter are described in grey text or icons whereas components which feature in this chapter are printed in bold, black font. The first and second testing session of the repeatability study are represented by the abbreviations S1 and S2 respectively. The first and second testing sessions of the fatigue study are represented by the abbreviations F1 and F2 respectively.

Table 6.1. Participant characteristics for repeatability and fatigue study. Anterior cruciate ligament intact control group (ACLI) and anterior cruciate ligament reconstructed group (ACLR), age weight and height reported as group mean ± standard deviation.

	Repeatability Study	Fatigue Study	
		ACLI	ACLR
n	10	10	10
Gender	Female	Female	Female
Age (yr)	21 ± 2	23 ± 5	24 ± 5
Weight (kg)	65 ± 9	65.1 ± 5.8	73.5 ± 9.4
Height (m)	1.70 ± 7	1.74 ± 0.04	1.74 ± 0.04
Sport	6 netball, 2 hockey, 2 football	7 netball, 2 hockey, 1 football	6 netball, 2 hockey, 1 football, 1 rugby
Level	10 University sports team players	3 international, 7 national	2 international, 4 national, 2 regional, 2 county
ACL graft type	NA	NA	Hamstring graft
Years since ACL reconstruction	NA	NA	5 ± 4

6.2.3 Data Collection

Lab set up

A twelve camera (Oqus 400) infra-red Qualisys system collecting at 200 Hz via Qualisys Track Manager (QTM, Qualisys AB, Sweden) was set up in the University Applied Biomechanics Lab. A video camera (Oqus 210c) and force plate (Kistler, Switzerland) were integrated to synchronously capture movements from a frontal perspective (24Hz) and record force data (2000 Hz) respectively (Figure 6.2).

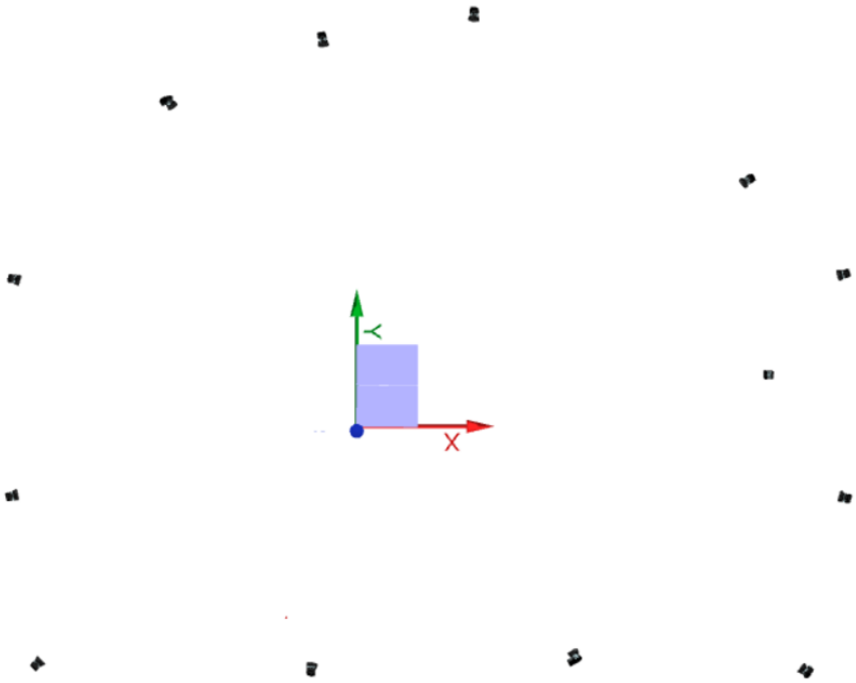


Figure 6.2. Schematic representing the laboratory set up from an aerial view. Force plates are indicated in lilac. Participants approached the higher of the two force plates by travelling parallel to the X-axis from the left before contacting the upper force plate and cutting 45 degrees. The Z axis was defined as the axis perpendicular to the floor of the lab

Data collection preparation

A lower-limb trunk marker set (Vanrenterghem et al., 2010) was applied for the collection of kinematic data. Individual markers (28, 16 mm diameter) were applied to the skin with double sided tape on the underside of the base of the marker. Kinesiology tape (Rock Tape, Essex, UK) was then placed around the ball of the marker to adhere to the top side of the marker base and surrounding skin, thus providing additional support and minimising the risk of marker loss with sweating. Four rigid clusters, with four markers apiece, were attached to the legs using double sided adhesive tape. Coban self-adherent wrap (3M, Bracknell, UK) was then also wrapped around each cluster to secure it to the leg. Participants were asked to put on a heart rate monitor (Polar H10, Polar Electro Ltd, Warwick, UK) and were familiarised with the BORG 15 grade rating of perceived exertion (RPE) scale (Borg, 1982). A static trial was collected, and then medial femoral condyle, malleolus and first metatarsophalangeal markers were removed so that they did not obstruct the participants' natural movements during testing. The static trial was used to measure the vertical distance between the greater trochanter and lateral malleolus markers to determine the leg length of each participant, as information that would be used later in the testing protocol. Markers remained in place for the duration on both testing sessions (S1 and S2 for the repeatability study and F1 and F2 for the fatigue study).

Warm-up

Participants completed a warm-up consisting of treadmill jogging at a range of speeds (5 minutes at a self-selected slow pace, 30 s at an intermediate pace and 10 s at a fast pace) and then were asked to perform any stretches that they would normally complete prior to participation in their sport. In the repeatability study, each participants' warm-up for S1 was recorded so that they repeated the same warm up prior to S2. Following this, the requirements of the movement tasks, which participants would later be asked to perform (i.e. cuts, drop-cuts and drop vertical jumps) were explained in a standardised fashion and demonstrated. Participants were then asked to fully familiarise themselves with the movements before testing began. This involved repeating each movement until the researcher was satisfied the participant was performing it at maximal effort and were consistently achieving the requirements of the task.

For the fatigue study, during familiarisation for the drop vertical jump, the height of a ball suspended from the ceiling was adjusted to a height that was only just reachable by the participant in the vertical jump. The aim of this was to stimulate maximum effort vertical jumps (Mok, Bahr and Krosshaug, 2017) throughout the fatigue cycles.

Testing protocol

Participants were asked to perform multiple repetitions of two different movement tests on each leg before and after an intervention of rest (repeatability study) or fatiguing exercise (fatigue study) (as detailed in Figure 6.1). The 45º cutting movements were performed first followed by 90º drop cuts. The drop cut movement was not relevant to the aims of this thesis so no data was analysed for this movement within this chapter. However, the drop cut movements did contribute to the overall load experienced by the athlete during the testing session so the details of the cutting movement, drop cut movement and fatigue protocol are outlined below.

Cutting

During movement familiarisation, a mark was placed on the floor in a position from which the participant was able to consistently contact the force plate within three steps. Participants received an instruction prior to each cutting trial indicating which foot they should place forward on this mark and in which direction they should cut. They were asked to perform the whole cutting movement at maximal intensity and to accelerate out of the cut along a path indicated by cones protruding at 45 degrees to the left or right of the direction of travel.

A total of 24 successful cuts were captured (12 on each side) in a randomised order. For a cut to be deemed successful, there had to be no obvious spotting of the plate, the cutting foot had

to cleanly strike the force plate and the participant had to remain within the designated cutting path for at least two steps after the cut. Due to space restrictions within the laboratory, the participants had 4 m after the cut in which to stop.

Drop cut

A 31 cm high drop box was positioned a leg length (defined here as the distance between the participant's malleolus and greater trochanter) behind the rear edge of the force plate (45 cm from the centre). Visual targets were marked on the floor using white electrical tape a leg length from the left and right edges of the force plate and participants were required to land at least as far as these marks on each drop cut. Participants were informed that they would receive an instruction prior to each movement trial indicating which foot they should stand on when on the box and in which direction they should cut. Participants were asked to leap down from the box onto the centre of the force plate with their free foot, cut to land on the other foot on or beyond the target line to their left or right, and try to maintain single leg stance until they had gained balance. Their hands were placed on their waist to challenge their balance and they were told to maintain a forward gaze throughout. A trial was deemed successful if the whole foot struck the force plate, the landing to the side touched or exceeded the target, hands remained on hips, and controlled balance was demonstrated in the single leg stance.

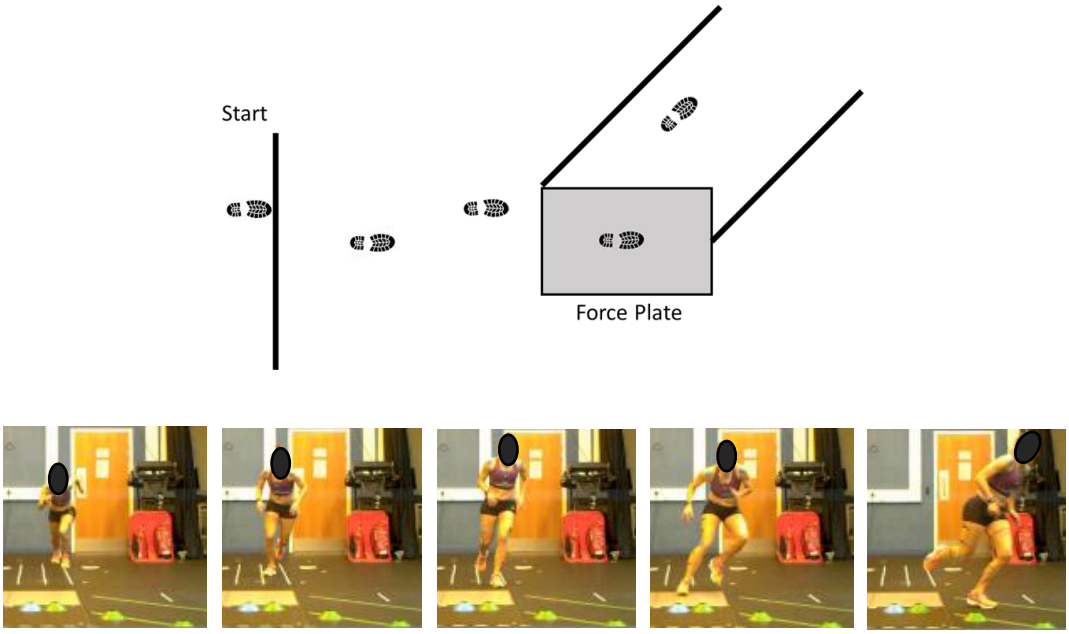


Figure 6.3. 45 degree cutting task step sequence for right leg contact change of direction task. The top image represents and aerial schematic. The bottom sequence of images show the frontal camera view of the task.

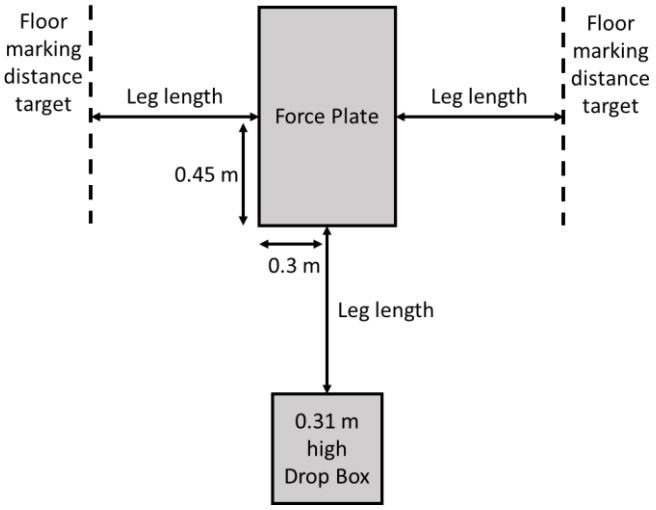


Figure 6.4. Schematic representing the laboratory set up for the drop cut.

Fatigue cycle

Participants in the fatigue study completed a series of fatigue cycles between testing sessions one and two. Gehring, Melnyk and Gollhofer (2009) stated that when investigating the effect of fatigue there are two categories of protocol available to the researcher; controlled or functional exercise protocols. For this study a protocol that mimicked the demands of match play was deemed important because controlled protocols often cause disproportionate fatigue in certain muscle groups, commonly those that elicit movement in the sagittal plane. James, Scheuermann and Smith (2010) also found that different fatiguing protocols, in their case cycling and running, had different effects on jump technique. Because of the potential importance of muscles that work outside of the sagittal plane for change of direction tasks and the importance of realistic technique changes for measuring coordination dynamics, the use of a more functional fatiguing protocol was deemed appropriate to address the aims of this study.

The particular protocol proposed was designed to provide an intermittent exercise stimulus, similar to that experienced by team sports players. Each cycle comprised five plyometric vertical drop jumps, with moderate rest periods (the time to walk from the front to the back of the drop jump box to remount) between jumps, followed by periods of high intensity short sprints. In order to complete the fatigue cycles, a 31 cm high box was positioned 45 cm behind the centre of the force plate and five cone targets were spread out around the central point of the two force plates (Figure 6.5).

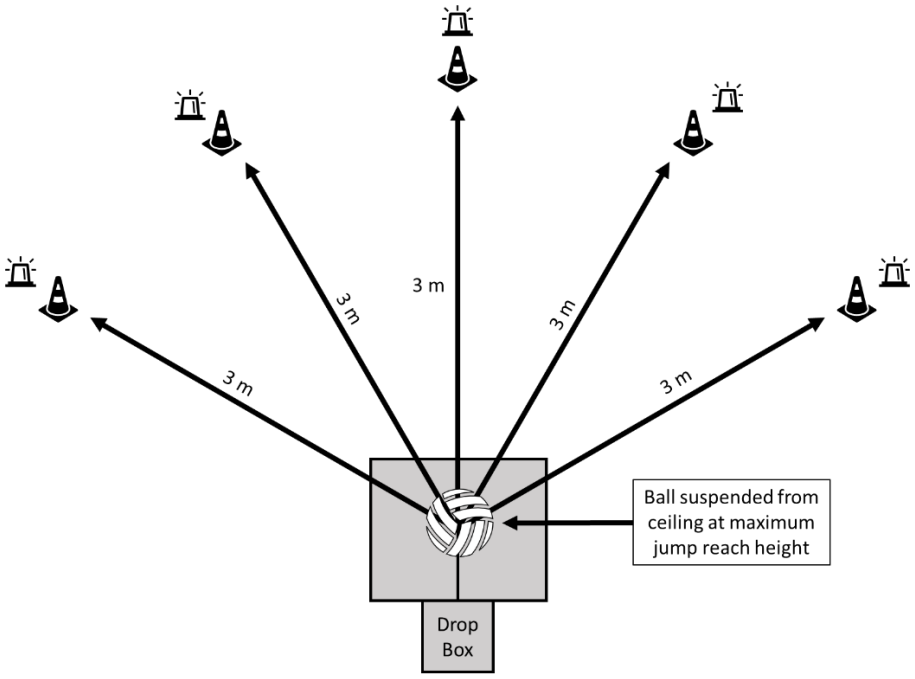


Figure 6.5. Schematic representing the fatigue cycle laboratory set up. A 31 cm high drop box (DB) was placed behind two force plates (grey). Target cones were set up 3 m from the centre of the force plate area with lights behind them that lit up in a randomised order and a ball was suspended above the force plates to encourage maximal jump efforts.

Drop jumps

Participants were instructed to descend from two feet off the box without jumping upwards. They landed with one foot on each force plate, aiming for a central anterior-posterior positioning on the plates, and then performed a maximal jump, reaching upwards with their arms, aiming to tap the ball which was suspended from the ceiling with both hands. They then landed again, with one foot on each plate and moved off the force plate to stand back on the drop box. This process was repeated five times within each fatigue cycle. After the fifth drop vertical jump, participants immediately started the change of direction spring and return task (Figure 6.5).

Change of direction sprint and return task

In each cycle, five cone targets had custom made lights placed behind them, which lit up on two occasions, in a randomised order. Participants were instructed to sprint to the lighted target as quickly as possible and then return to the force plate maintaining a forward view by travelling sideways and/ or backwards. When the participant first touched the force plate the researcher pressed a button and the next randomly chosen target would light up. This meant that the total load of each cycle was approximately: 30 m short sprint, 30 m sideways/backwards and 5 drop jumps. Thus the total load of all six fatigue cycles was 180 m

forwards acceleration, 150 m side-stepping/backward jogging and 30 jumps. Because of the multisport backgrounds of the participants and the demands of different playing positions within these sports, it was not possible to match the protocol to those faced by each participant in their respective sport and position. However, the high intensity distance covered (running and sprinting) in the 6 cycles of fatigue are comparable to those reported for different playing positions (36 - 440 m running, 17 - 139 m sprinting) during one quarter of a netball game (Davidson and Trewartha, 2008) . Due to the difficulties in standardising functional fatiguing protocols, heart rate and RPE measures were collected so that post-hoc comparisons could be made with match demands to inform the interpretation of results.

6.2.4 Data Processing

A total of thirteen dependent variables were analysed in this chapter to include eight measures of coordination variability (four time series, and their averages across time) and five joint angles (Table 6.2). A flowchart of the analysis for the calculation of the three subsets of variables (coordination variability averaged across the stance phase of the cut ($\overline{V}$), coordination variability time series (V) and mean joint angle time series ($\bar{J}$)) and their application is presented in Figure 6.6. The coordination variability measures were the main variables of interest. Mean joint angle measurements were included for the repeatability study only in order to make comparisons with the repeatability of cutting movements measured in other research.

Table 6.2. Overview of dependent variables within Chapter 6. The variables are divided into three subsets: average coordination variability across the normalised time period ($\bar{V}$), coordination variability time series (V) and mean joint angle time series ($\bar{J}$).

Subset	Variables
$\bar{V}$	(1) Hip flexion/extension – Knee flexion/extension (H_{FE}-K_{FE}) (2) Hip internal/external rotation – Knee flexion/extension (H_{IER}-K_{FE}) (3) Hip internal/external rotation – Knee internal/external rotation (H_{IER}-K_{IER}) (4) Knee flexion/extension – Knee ab/adduction (K_{FE}-K_{AA})
V	(1) Hip flexion/extension – Knee flexion/extension (H_{FE}-K_{FE}) (2) Hip internal/external rotation – Knee flexion/extension (H_{IER}-K_{FE}) (3) Hip internal/external rotation – Knee internal/external rotation (H_{IER}-K_{IER}) (4) Knee flexion/extension – Knee ab/adduction (K_{FE}-K_{AA})
$\bar{J}$	(1) Hip Flexion/Extension (H_{FE}) (2) Hip Internal/External Rotation (H_{IER}) (3) Knee Flexion Extension (K_{FE}) (4) Knee Ab/Adduction (K_{AA}) (5) Knee Internal/External Rotation (K_{IER})

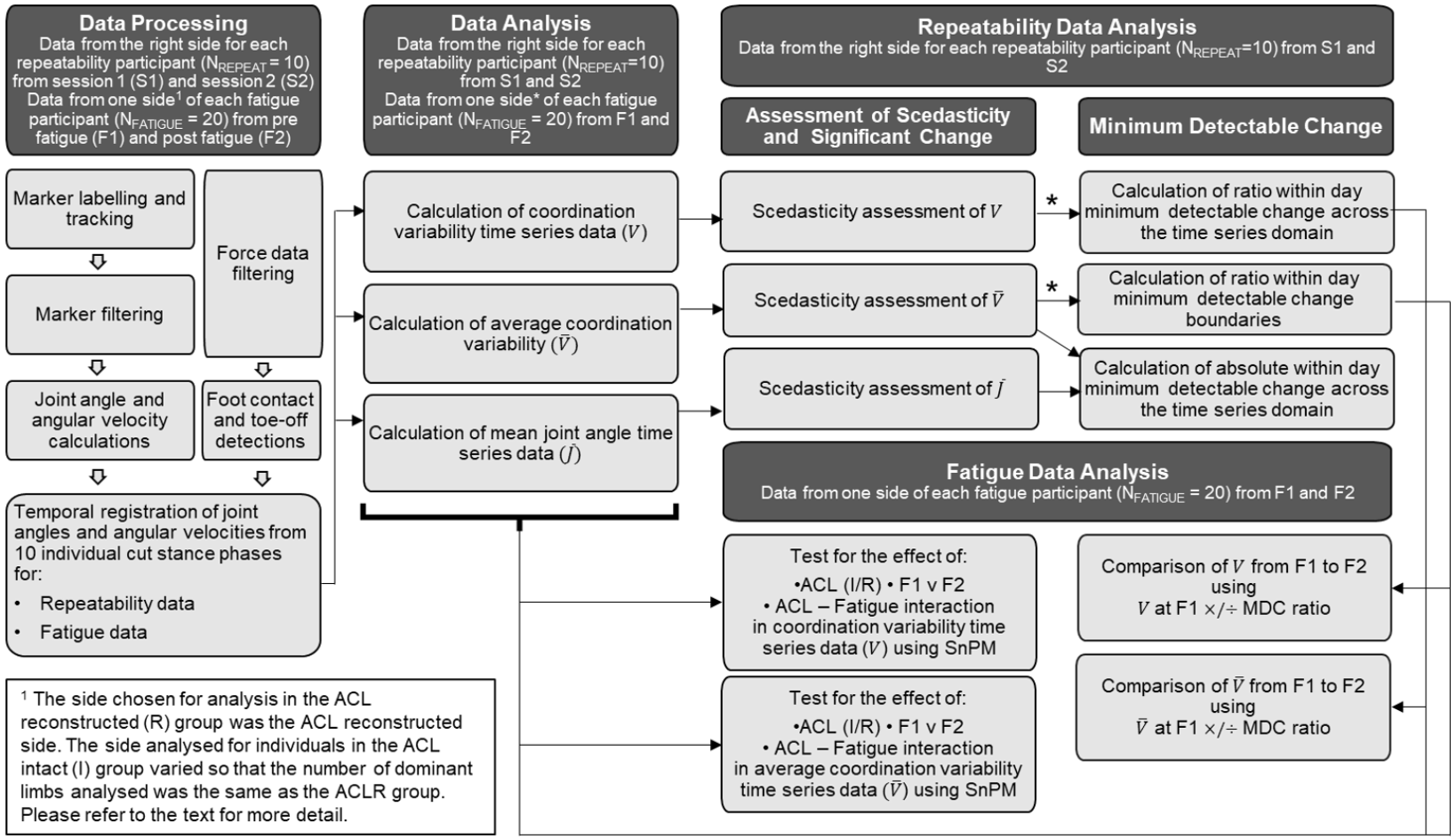


Figure 6.6. Schematic overview of the data analysis process for Chapter 6. Data from session 1 and session 2 of the repeatability (S1 & S2) and fatigue (F1 & F2) study were processed in the same way and were then used separately and in combination to meet the aims of the study. The * represents that some variables were observed to be heteroscedastic and became more homoscedastic following a log transform of the data. Consequently, alternative calculations were performed to compute the minimum detectable change (MDC) as a ×/÷ ratio value instead of the more commonly seen ± absolute variant. The supporting results behind this choice can be found in section 6.3.1.

Coordination couplings were chosen based upon existing findings published on coordination variability in cutting movements and their relation to ACL injury mechanisms. The following four couplings were selected: hip flexion/extension – knee flexion/extension and hip internal/external rotation – knee flexion/extension (both of which have been found to be greater in unanticipated than anticipated cutting (Weir et al., 2019), hip internal/external rotation – knee internal/external rotation (found to be lower following hamstring fatigue, (Samaan et al., 2015a)) and knee flexion – knee ab/adduction (found to be lower in a group that had had an ACL reconstruction compared to those without ACL injury (Pollard et al., 2015).

In the repeatability and fatigue study a number of variables were also identified that were linked to the physiological status of the participant and their performance of the cutting task. Whilst it was not possible to control these during data collection, their values were monitored to understand if the physiological status of the participants and their individual performances of the cutting task were significantly different between the repeated testing sessions. The physiological markers chosen were heart rate and RPE. The cutting performance measures were velocity prior to the cut, velocity coming out of the cut and the change of direction elicited during the stance phase of the cut. These parameters were all estimated using the pelvis segment centre position and velocity (Equations 6.1 to 6.6).

In the repeatability study both the physiological and cut performance measures were considered control variables as the aim was to measure the consistency of coordination variability measurements under repeated conditions. In the fatigue study, the cutting performance measures were monitored as control variables but the physiological measurements served as independent variables and indications of the participants' responses to the fatigue protocol.

In the processing of the fatigue study it became clear that some trials could not be used as key markers had been obscured from view of the cameras in certain trials. This was the case for three of the ten participants in the repeatability study and for five of the twenty participants in the fatigue study. All but one participant had ten cutting trials available across both the repeatability and fatigue study therefore data were processed using ten cuts. One participant (P17 ACLI group) only had nine cuts available for one of the data collection sessions therefore pre and post fatigue data was processed using nine trials only for both F1 and F2 for this participant.

For the repeatability study the data collected from each participant's right leg was used in the analysis. In the fatigue study, the leg chosen for analysis in the ACLR group was the ACL reconstructed leg. This was the dominant leg for seven of the ten participants, defined as the

leg they self-selected they would choose to kick a football furthest with. To ensure the number of dominant and non-dominant limbs analysed was equal between groups, three participants were randomly selected from the ACLI group to have their non-dominant limb used in analysis and the data from the dominant side was used for the remaining seven of that group.

An automatic identification model was used to assign marker trajectories for each movement repetition in Qualisys (Qualisys AB, Sweden). Marker trajectories were then exported to Visual3D (v6, C-Motion, USA) alongside the raw force data. In Visual 3D, marker trajectories and the analogue force signals were filtered using a low-pass bidirectional 2nd order Butterworth filter, with a cut off of 20 and 200 Hz respectively. Segments and joints were defined and joint angles and angular velocities were calculated as outlined in Chapter 5.2.4. The following variables were then exported to MATLAB (R2018b, Natick, USA): Force data were exported for detecting foot contact events, the centre of mass position of the pelvis and its velocity were exported to calculate performance metrics of the cut and joint angles and angular velocities for the lower limbs were exported for the calculation of joint angle and coordination variability. All exported kinematic variables were stored as separate columns of a matrix (**A**), where each row represented a separate frame of data (f). In MATLAB the force data was down sampled to 200 Hz and the time of contact with the force plate (α) was determined as the frame index where force first exceeded a threshold of 10 N. The frame index of the end of the stance phase of the cut (β) was the last frame before the force fell below the 10 N threshold. These time points defined the start and end point of the foot contact phase of the cut.

The absolute velocity of the pelvis prior to foot contact (Equation 6.1), the absolute velocity of the pelvis after foot contact (Equations 6.2) and the change in the angle of travel from pre to post cut (Equations 6.3, 6.4 and 6.5) were calculated in the XY (horizontal) plane, where P_X is the position of the pelvis along the x-axis, P_Y is the position of the pelvis along the y axis, $\dot{P_X}$ is the x component velocity of the pelvis segment and $\dot{P_Y}$ is the y component velocity of the pelvis segment. The calculations were performed for data from every cycle, session and participant.

$$\dot{P}_{IN} = \sqrt{\left(\dot{P}_{X_{\alpha-1}}\right)^2 + \left(\dot{P}_{Y_{\alpha-1}}\right)^2} \tag{6.1}$$

$$\dot{P}_{OUT} = \sqrt{\left(\dot{P}_{X_{\beta+1}}\right)^2 + \left(\dot{P}_{Y_{\beta+1}}\right)^2} \tag{6.2}$$

$$\theta_{IN} = \tan^{-1}\left(\frac{P_{X_{\alpha-1}} - P_{X_{\alpha-2}}}{P_{Y_{\alpha-1}} - P_{Y_{\alpha-2}}}\right) \quad (6.3)$$

$$\theta_{OUT} = \tan^{-1}\left(\frac{P_{X_{\beta+2}} - P_{X_{\beta+1}}}{P_{Y_{\beta+2}} - P_{Y_{\beta+1}}}\right) \quad (6.4)$$

$$\theta_{CHANGE} = \theta_{OUT} - \theta_{IN} \quad (6.5)$$

Average absolute velocity prior to foot contact ($\bar{P}_{IN}$), average absolute velocity after foot contact ($\bar{P}_{OUT}$) and average change in direction ($\bar{\theta}_{CHANGE}$) were then calculated for each participant across the ten cutting trials (c = 1,…,10 for all but one participant, as explained previously) using the equation for the arithmetic mean, as demonstrated for $\bar{P}_{IN}$ in Equation 6.6. The calculations were performed for every session and participant.

$$\bar{P}_{IN} = \frac{\sum_{c=1}^{C} \dot{P}_{IN}}{C} \quad (6.6)$$

The joint angle and joint angular velocity data for each variable were cropped to contain the data between the first foot contact (α) and the last frame before the foot left the force plate (β):

$$\mathbf{B}_c[f] = \mathbf{A}[\hat{\alpha}_c] \qquad \hat{\alpha}_c \in [\alpha_c, \alpha_c + 1, \alpha_c + 2 \ldots \beta_c] \quad (6.7)$$

The resulting output was a collection of 20 matrices ($\mathbf{B}_c$) of varying length containing the joint angle and angular velocity data from each gait cycle.

The average number of frames per contact from the first data collection session in both studies (combined N=30) was 40 ± 6 (mean ± standard deviation). Segment and joint data from each

stance phase were temporally registered (indexed by t = 1,…,51) to represent 0% to 100% of the stance phase of the cut in 2% increments.

6.2.5 Data Analysis

Coordination variability

The velocity ellipse method was applied as described in Chapter 4, Section 4.2.3 to calculate coordination variability time series for couplings: H_{FE}-K_{FE}, H_{IER}-K_{FE}, H_{IER}-K_{IER}, K_{FE}-$K_{AA.}$ using angular velocity (ω) variables as the inputs to equations. In brief, this involved the following calculation steps based on similar methods presented by Duarte and Zatsiorsky (2002) and Mullineaux (2017):

1) A covariance matrix [2 2] was formed from ω_x and ω_y at each temporal node (Equations 4.7 and 4.8).

2) Eigenvalues were computed from each covariance matrix (Equations 3.9 to 3.13)

3) Ellipse axes were formed from the root of each eigenvalue scaled according to k (Equation 3.14 and 3.15), so that the size of the ellipse was not affected by the number of stride cycles collected (Schubert and Kirchner, 2014; Mullineaux, 2017).

4) The product of the ellipse axes was multiplied by pi to define an ellipse area (V) within which 95% of future observations should fall (Equation 3.16). Ellipse area served as the measure of coordination variability: the greater the area of the ellipse, the more variable the coordination variability was.

Coordination variability (V) was then averaged across the stance phase of the cut by taking the arithmetic mean across the gait cycle (indexed by t = 1,…,51):

$$\bar{V} = \frac{\sum_{t=1}^{T} V_t}{T} \tag{6.8}$$

This was repeated for data from each participant and each session.

Mean joint angles

The five joint angles that were used in the calculation of the couplings chosen for coordination variability analysis were also extracted (i.e. hip flexion/extension, hip internal/external rotation, knee flexion/extension, knee ab/adduction, knee internal/external rotation) and averaged across repetitions of the cutting movement (indexed by c = 1,…,10 for all but one participant as explained previously) were calculated for each individual in each data collection session:

$$\bar{J} = \frac{\sum_{c=1}^{C} J_c}{C} \tag{6.9}$$

6.2.6 Repeatability Specific Methods

The methods of estimating repeatability used in this study are largely based on the techniques suggested by Bland and Altman (1996a) with the minimum detectable change (MDC) representing the same measure that Bland and Altman first referred to as 'repeatability'. The MDC was chosen as it calculates a range of values within which 95% of the differences between two measurements taken on the same person should fall within. Thus, if the difference between two measurements does not exceed the upper or lower boundary of the MDC, the difference can be assumed to be a result of random fluctuations.

To calculate the MDC a minimum of two repeated measures are required that were taken under the same conditions in a sample population. For the MDC calculations to be valid, it is important to first check that no systematic changes occurred within the group between those sessions. The next step is to understand whether the within participant variance between the repeated sessions is consistent or varies across a range of values (the scedasticity). The scedasticity of the data is important as it determines the most appropriate methods to calculate the MDC. The exact methods used to perform these steps within this chapter were as follows:

Systematic change

Within a repeatability study, it is important to ensure that the same conditions are replicated in both repeated sessions to minimise systematic bias (Atkinson and Nevill, 1998). Actions can be taken to help reduce systematic bias (e.g. by allowing recovery time between movements, providing consistent motivational cues and allocating sufficient task familiarisation time) but it is not possible to guarantee systematic bias has been eliminated by taking these precautions alone. Measuring the consistency of other variables (additional to the dependent variable) that are relevant to how each participant completed the task and their physiological status in each session can therefore help understand what was or was not consistent between those sessions. In the repeatability study no systematic changes were expected to occur between the first (S1) and second session (S2) either in physiological, cut performance or coordination variability measures.

To check whether any systematic changes were observed, statistical non-parametric mapping (SnPM) repeated measures Analysis Of Variance (ANOVA) tests were performed on the repeatability data. Non-parametric tests were chosen throughout this chapter as they do not

assume the data to be parametric and should therefore be more robust as they are appropriate for use on both parametric and non-parametric data, although their results have been found to be largely very similar to their parametric counterparts (Pataky, Vanrenterghem and Robinson, 2015). In the testing protocol, heart rate and RPE data were collected at multiple time points throughout the testing session to provide information as to the physiological responses to the contents of the session. Only the heart rates and RPEs measured immediately after the cut tasks had finished were used for statistical comparison. These were selected as a single indication of the intensity at which the cutting movements were performed to avoid performing additional unnecessary statistical comparisons. The remaining heart rate and RPE data will be reported descriptively (i.e. with no statistical analysis performed).

Specifically, the SnPM repeated measures ANOVA was computed as follows: a t statistic was computed for comparisons of discrete data or a t-statistic trajectory was computed for each temporal node of the time-series data. The permutation method (Nichols and Holmes, 2002) summarised comprehensively in (Pataky, Vanrenterghem and Robinson, 2015) was used to generate the tcrit-threshold statistic (F*) from 10,000 permutations ($\alpha = 0.05$). When the t statistic exceeded this threshold, individual probabilities were calculated for the likelihood that the result could have been caused by a random process. This approach is based on Random Field Theory (Adler and Taylor, 2007). The analysis was completed using open source code (Pataky, 2019). No significant changes were hypothesised to occur between S1 and S2 as every effort was made to replicate conditions between testing sessions, and measurement errors were minimised by keeping the same markers in place between sessions.

Scedasticity

The methods used to assess scedasticity and significant change in this chapter were very similar to those in in Chapter 5, Section 5.2.6, but have been reported here again for convenience:

Scedasticity refers to the distribution of error terms. When error terms are distributed randomly with constant variance, the spread of the error terms is referred to as homoscedasticity. Heteroscedasticity is when error terms are not equal across the range of values. If the error terms of a dataset are heteroscedastic, traditional parametric statistical assumptions are violated and alternative statistical approaches may be necessary. In the specific instance of repeatability investigations with two repeated measures, if data is homoscedastic then the absolute differences observed between repeated measurements would be the same, regardless of the magnitude of the measurements. Thus, any indicator of expected variation between repeated measurements can be expressed as ± about the measured value. In heteroscedastic data the relationship between the absolute difference between measurements

and the mean value can take many different forms. One possible form that has been observed in other sport science data is that the absolute difference between measurements is greater for larger values (Atkinson and Nevill, 1998). In these circumstances, it is therefore not appropriate to have a fixed ± variation applied to all values, and so expected variation must be represented as a ratio. Any value of the measured data is multiplied by the ratio to estimate the upper limit of the expected variation or divided by the ratio to estimate the lower limit of expected variation. The ratio is therefore represented as $\times$ / $\div$ and has a minimum possible value of one. A ratio of one would indicate perfect repeatability of the measurement.

To check whether a dataset of repeated measures demonstrated homo- or hetero-scedastic properties and determine the most appropriate method for calculating the MDC for each dependent variable a process of steps was followed (Figure 6.7). The process was largely based on the methods presented in Bland and Altman (1996a) and (Bland and Altman, 1996b) and further details of the individual steps and calculations are provided later in the chapter. There are several examples within sport science research where the methods presented by Bland and Altman have been applied to discrete measures, but there is little or no advice for its application to time series data. In this chapter, the scedasticity of time series data was assessed by applying MDC calculations at each temporal node and combining these into a time series of MDC values.

Decision of constant variance

A combined qualitative and quantitative approach was used to decide whether the spread of variance was consistent across the range values measured in the process of assessing the scedasticity of each dependent variable (Figure 6.7). The qualitative approach was to visually assess whether the within participant differences between sessions were constant across all within participant mean values (e.g. simulated example data in Figure 6.8A) or if they were not consistent across the range of values (e.g. simulated example data in Figure 6.8B). In the quantitative approach, a Kendall rank correlation test was performed (Kendall, 1938). The Kendall rank test ranks each observation for each variable (in this example, one list of ranking for the within participant mean, and another for the within participant between session difference). The Kendall correlation (τ) is high (a maximum of 1) when each observation has the same or similar rank for both variables, low (a minimum of -1) when the ranks for each variable are opposite and 0 when there is no correlation between the ranks. A p value was also calculated to determine if the correlation is significant ($\alpha < 0.05$). Homoscedastic data would be expected to have a non-significant τ value close to 0 (e.g. τ = -0.01 and p = 0.66 for the simulated example in Figure 6.8A). The inclusion of the qualitative approach is important as the Kendall Rank test is only appropriate for testing linear correlations.

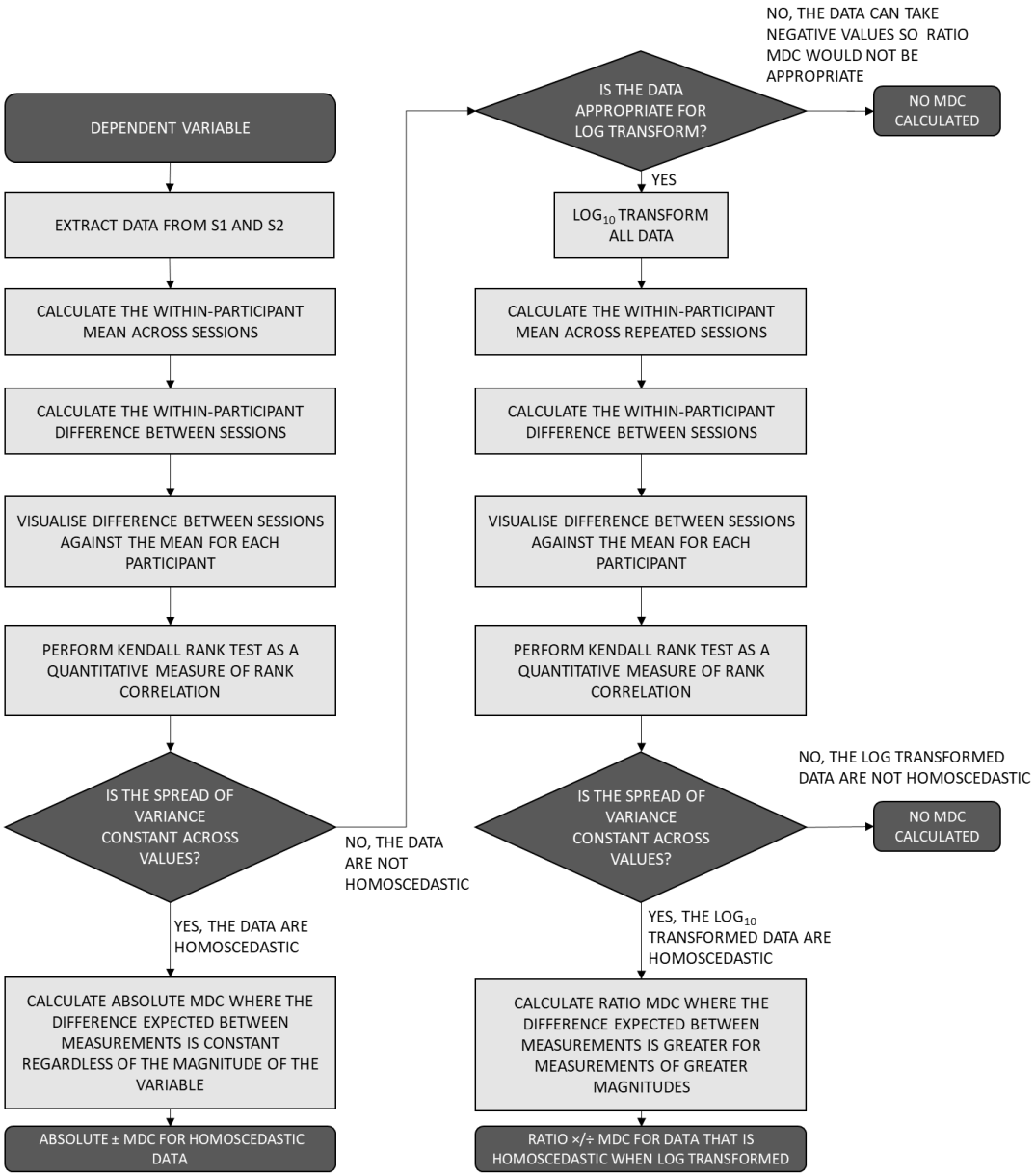


Figure 6.7. Flow diagram of the steps and decision processes taken to identify the scedasticity of the cutting repeatability data. This process informed the decision of whether to calculate a Minimum Detectable Change (MDC) value or ratio.

Calculation of Minimum Detectable Change

The appropriate steps for calculating the MDC depend on whether the data are homoscedastic either in their raw form or following a $\log_{10}$ transform. Data that is homoscedastic in its raw form can be used to calculate an MDC. This MDC can then be used to interpret whether an observed difference between two new measurements (M1 and M2) is meaningful. The absolute MDC is added to and subtracted from M1 to create a range within which future

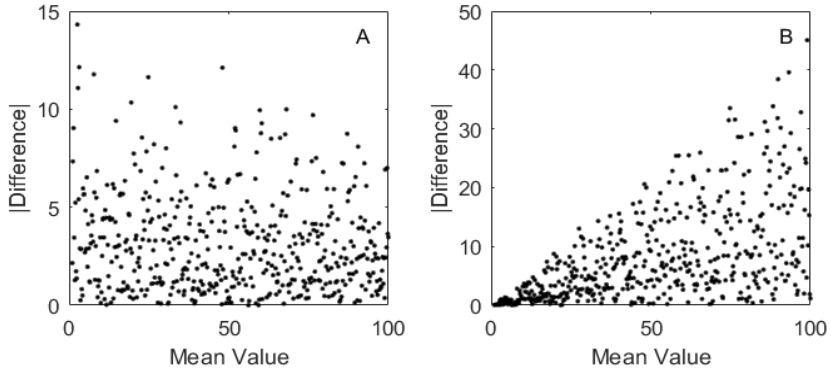


Figure 6.8. Example demonstrating homoscedastic (A) and heteroscedastic (B) data. In the homoscedastic data, the absolute differences between repeated measures remains relatively constant across the entire range of mean values. In the heteroscedastic example the mean absolute difference is not constant across the range of mean values. In this example the absolute differences start small and increase as the mean value becomes larger.

repeated measurements could be expected to fall (e.g. Figure 6.9A). Conversely, data that is not homoscedastic in its raw form but is following a $\log_{10}$ transform must be processed in a different way to calculate a MDC ratio. M1 is multiplied by the MDC ratio to create the upper boundary of the MDC and divided by the MDC ratio to create the lower boundary about M1. This also creates a range within which future measurements could be expected to fall but the range expected above a measurement is greater than the range expected below, and greater variance is expected for measurements of larger magnitudes (e.g. Figure 6.9B).

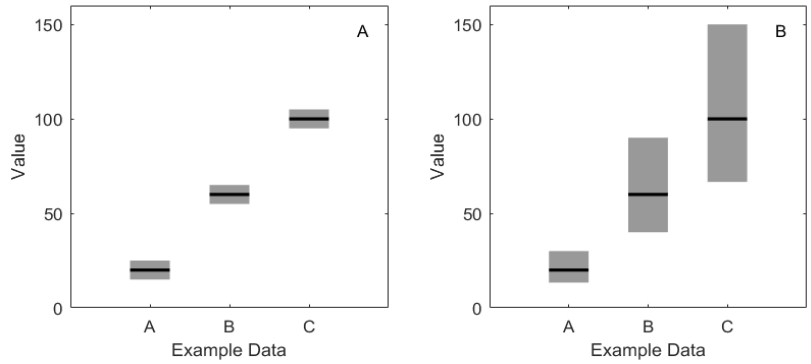


Figure 6.9. Example application of an absolute Minimum Detectable Change (MDC) and an MDC ratio. An absolute MDC of ± 5 (grey shaded areas, subplot A) was applied to three pieces of example data (A = 20, B = 60, C = 100, indicated with black lines). This is compared to a ratio MDC of ×/÷ 1.5 (grey shaded area, subplot B) applied to the same example data. If a second measurement were taken for example data A, B and C and plotted on the same graphs, if the second measurement was situated within a the shaded MDC area, the difference between those two measurements is likely to be the result of fluctuations in the measurement. If the second measurement exceeded the shaded areas in a positive/negative direction this would suggest that a change was observed which was greater than the fluctuations that we expect to observe in the measurement.

Homoscedastic data

For homoscedastic data a ± MDC value (MDCV) was calculated across the participant group (indexed by p = 1,…,10) using data from session 1 (S1) and session 2 (S2). This has been demonstrated for the specific example of mean joint angle across ($\bar{J}$):

$$MDCV = 1.962 \cdot \sqrt{2} \cdot \sqrt{\frac{\sum_{p=1}^{P}(\bar{J}_{S2,p} - \bar{J}_{S1,p})^2}{2P}} \quad (6.10)$$

To use the MDCV in practice, a baseline measurement is collected ($\overline{J'}$), an intervention is conducted, and another measurement is taken ($\overline{J''}$). The user wishes to understand whether the change they observed between $\overline{J'}$ and $\overline{J''}$ is greater than the minimum detectable change. The MDCV can then be used to calculate upper and lower MDC boundaries about $\overline{J'}$ (Equation 5.7 & 5.8). If $\overline{J''}$ is greater than the upper boundary or less than the lower boundary, then the change observed was greater than the minimum detectable change.

$$UpperMDC = \bar{J}' + MDCV \quad (6.11)$$

$$LowerMDC = \bar{J}' - MDCV \quad (6.12)$$

Homoscedastic data following log transform

In cases where the log transformed data was found to be homoscedastic, an MDC ratio (MDCR) was calculated. This process has been demonstrated for the specific example of coordination variability time series measurements (V) in equations 6.13 to 6.18. For time series measures, the same calculations were applied for data from each time point. The first step was to $\log_{10}$ transform all data:

$$\hat{V} = \log_{10}(\mathrm{V}) \quad (6.13)$$

and use the transformed data as an input for calculating the standard error of measurement ($\hat{S}$) across the participant group:

$$\hat{S} = \sqrt{\frac{\sum_{p=1}^{P}(\hat{V}_{S2,p} - \hat{V}_{S1,p})^2}{2P}} \quad (6.14)$$

$\hat{S}$ was then inverted to transform from the logarithmic scale back to the natural scale:

$$\sigma_g = 10^{\hat{S}} \quad (6.15)$$

This process outputs a ratio that can be referred to as the geometric standard deviation (σ_g). Bland and Altman then manipulated σ_g to encompass 95% of the data by raising σ_g to the power of 1.96 (Bland and Altman, 1996b). In this thesis this step of the method has been extrapolated to the context of the MDC measure by raising σ_g to the power of $1.96 \cdot \sqrt{2}$ (Equation 6.16). This accounted for encompassing 95% of the differences between two measures.

$$MDCR = (\sigma_g)^{1.96 \cdot \sqrt{2}} \quad (6.16)$$

To use the MDCR in practice, a baseline measurement is collected (V'), an intervention is conducted, and another measurement is taken (V''). The user wishes to understand whether the change they observed between V' and V'' is greater than the minimum detectable change. The MDCR can then be used to calculate upper and lower MDC boundaries about V' (Equation 6.17 and 6.18). If V'' is greater than the upper boundary or less than the lower boundary, then the change observed was greater than the minimum detectable change.

$$UpperMDC = V' \cdot MDCR \quad (6.17)$$

$$LowerMDC = \frac{V'}{\mathrm{MDCR}} \quad (6.18)$$

6.2.7 Fatigue Study Specific Methods

Statistical Analysis

The first step in the fatigue study analysis was to test whether the physiological measures were different prior to fatigue (F1) compared to post fatigue (F2) as means of supporting whether fatigue status had changed between the sessions and whether there was any difference between

the ACLI and ACLR group regarding the magnitude of change in physiological measures between F1 and F2. The second was to understand whether there had been a change in cut performance measures from F1 to F2, or if cut performance was different between the two groups. This was to provide evidence as to whether differences in the cut performance (either between F1 and F2 or between the ACLI and ACLR groups) might be mediating or moderating factors in any changes observed in coordination variability.

To perform these steps a SnPM mixed model ANOVA test was performed for the physiological and cut performance variables. It was hypothesised that there would be no significant differences between groups, nor an interaction effect for both physiological measures (heart rate and RPE) and cut performance measures (pre contact velocity, post cut velocity and change of direction). This was because both ACLI and ACLR groups were performing at high levels without restriction due to injury at the time of testing. A statistically significant increase was expected in physiological measures between F1 and F2 but measures of cut performance were expected to stay the same. This is because the fatigue stimulus was designed to place a similar burden in volume as one quarter of a netball game in a condensed period and thus provided a demanding physiological stimulus. However, the ability of the group was deemed high enough that an obvious performance decrement in cutting was not expected to be observed.

The primary aim of the fatigue study was to understand the effect of fatigue and prior injury history on coordination variability (the dependent measure) during cutting and the SnPM mixed model ANOVA was also used as a statistical test of this. Significantly greater coordination variability was hypothesised in the ACLR group compared to the ACLI group, as this had been observed in previous literature (Pollard et al., 2015). A significant decrease in coordination variability was also predicted as a result of fatigue, particularly in the first half of the stance phase, as had been observed by Samaan et al. (2015a). Because the ACLR group were predicted to have greater starting variability compared to ACLI it was also predicted that the decrease in coordination variability that was predicted in response to fatigue would be greater in the ACLR group compared to the ACLI group.

The details of the SnPM mixed model ANOVA used to test for statistical tests on the physiological (independent), cut performance (control) and coordination variability (V and $\bar{V}$, dependent) variables was as follows: 10,000 permutations were performed and α was set at 0.05. The mixed model generated three critical thresholds (F*); one for each effect. Effect A represented whether there was a significant difference between the groups (ACLI and ACLR), effect B tested is there was a significant effect of fatigue and effect C tested if the response each group had to the fatigue protocol was significantly different.

Comparison of fatigue related changes and ACLR vs ACLI group differences using the MDC

In order to understand the magnitudes of change observed within individuals in response to the fatigue protocol, coordination variability was plotted for each individual and compared to the MDCs calculated within the repeatability study. This would inform whether changes observed in response to fatigue were greater than those observed due to fluctuations and variability between performances in the repeatability study.

6.3 Results

6.3.1 Repeatability Study

Significant change and scedasticity

Control variables

Heart rate and RPE were seen to increase from the measurement taken prior to the cutting movements (pre) compared to the middle point of the cutting task (during) and immediately once data for all 24 cuts had been collected (post, Figure 6.10). Only one time point from the physiological variables was chosen for statistical comparison, which was the time point immediately after the 24 cuts had been completed in each condition (post S1 cuts and post S2 cuts). At this time point, heart rate and RPE were not significantly different [S1 HR: 146 ± 16, RPE: 12 ± 1, S2 HR: 143 ± 18, RPE: 11 ± 2] as per the results of the repeated measures ANOVA (HR: $p = 0.436$, RPE: $p = 0.115$).

No significant group changes were observed in cut performance measures between sessions (Velocity In: $p = 0.740$, Velocity Out: $p = 0.123$, Change in direction: $p = 0.675$). The largest changes observed in any individual were of 0.25 $m \cdot s^{-1}$ (decrease) for velocity in, 0.25 $m \cdot s^{-1}$ (increase) for velocity out and 8º (increase) for direction change.

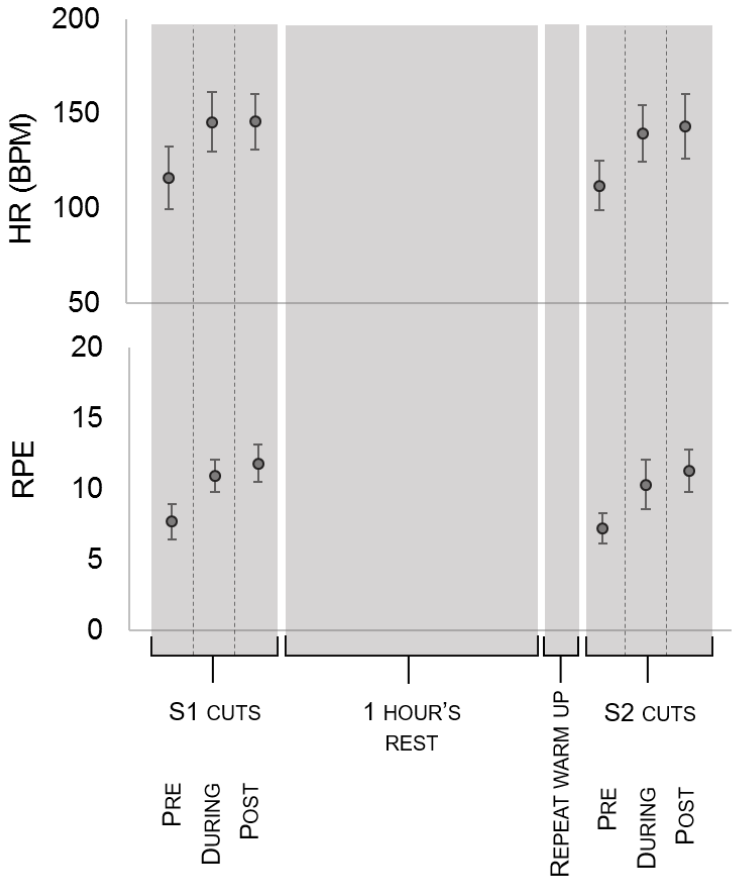


Figure 6.10. Heart rate (HR) and Rating of Perceived Exertion (RPE) throughout the different stages of the cutting repeatability testing protocol. The standard deviation is indicated by an error bar and the time that each data point was collected corresponds to the heart rate and RPE measurement indicators in Figure 6.1 for the repeatability protocol.

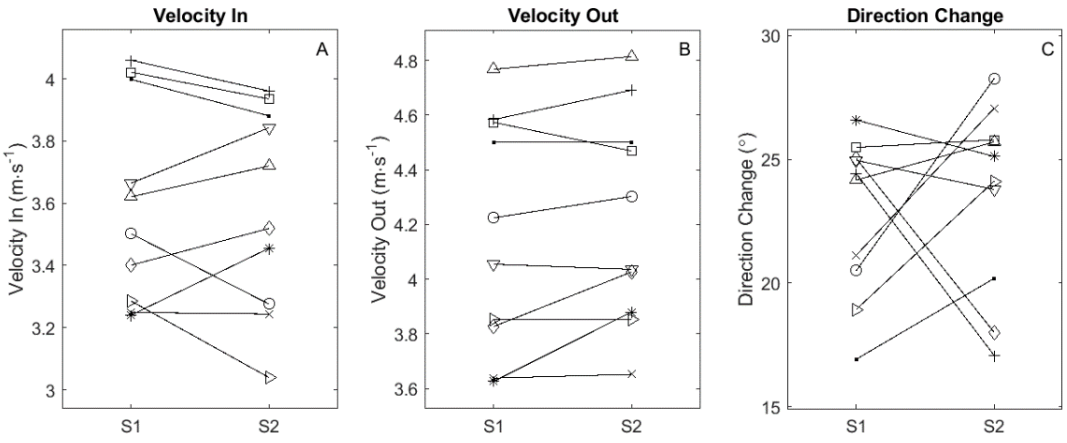


Figure 6.11. Changes in control variables between sessions. A) Pelvis velocity prior to foot contact B) Pelvis velocity after foot contact and C) Change of direction between S1 and S2 for each individual participant (represented by different markers).

Coordination variability

No significant changes were detected between the first (S1) and second round of testing (S2) for any of the four coordination variability couplings in either their average ($\bar{V}$, Table 6.3) or time series (V) forms (Figure 6.12).

Table 6.3. SnPM mixed model ANOVA results (α = 0.05) comparing average coordination variability ($\bar{V}$) between S1 and S2. Significant differences (p < 0.05) are marked (*).

Coupling	$\bar{V}$ at S1 ($^{\circ 2}\cdot s^{-2}$)	$\bar{V}$ at S2 ($^{\circ 2}\cdot s^{-2}$)	p value
H_{FE}–K_{FE}	54900 ± 25100	55100 ± 21200	0.973
H_{IER}–K_{FE}	84000 ± 39100	91400 ± 29600	0.471
H_{IER}–K_{IER}	109400 ± 52500	105200 ± 33000	0.785
H_{FE}–K_{AA}	79100 ± 55100	91100 ± 81700	0.526

A visual trend of heteroscedasticity could be seen for the mean hip flexion/extension – knee flexion/extension coordination variability across the gait cycle (Figure 6.13A) and for all four coordination variability couplings of the time series data in Figure 6.14. The visual trends were supported by τ correlation coefficients in excess of 0.395.

Following log transformation of the data, average coordination variability was qualitatively more homoscedastic for hip flexion/extension – knee flexion/extension, hip internal/external rotation – knee flexion /extension, and knee flexion extension – knee ab/adduction than in the untransformed data (Figure 6.15A, B and D compared to Figure 6.13 A, B and D). For these couplings, τ coefficients indicated less correlation (i.e. their value was closer to 0) between the mean value and the absolute difference in the log transformed data than in the data that had not been transformed. For hip internal/external rotation – knee internal/external rotation the data appeared less heteroscedastic in the untransformed data than the log transformed data and the τ correlations supported this (Figure 6.13C compared to Figure 6.15C). Therefore an MDC Ratio (×/÷) was chosen as the best method to represent repeatability for hip flexion/extension – knee flexion/extension, hip internal/external rotation – knee flexion /extension, and knee flexion extension – knee ab/adduction but an MDC Value (±) was deemed most appropriate for hip internal/external rotation – knee internal/external rotation. In the coordination variability time series, a clear change was observed for all four couplings following log transform whereby the data appeared to be more homoscedastic and this was supported by tau values close to zero in the log transformed data (Figure 6.16). MDC Ratio time series were therefore calculated for all coordination variability joint coupling time series.

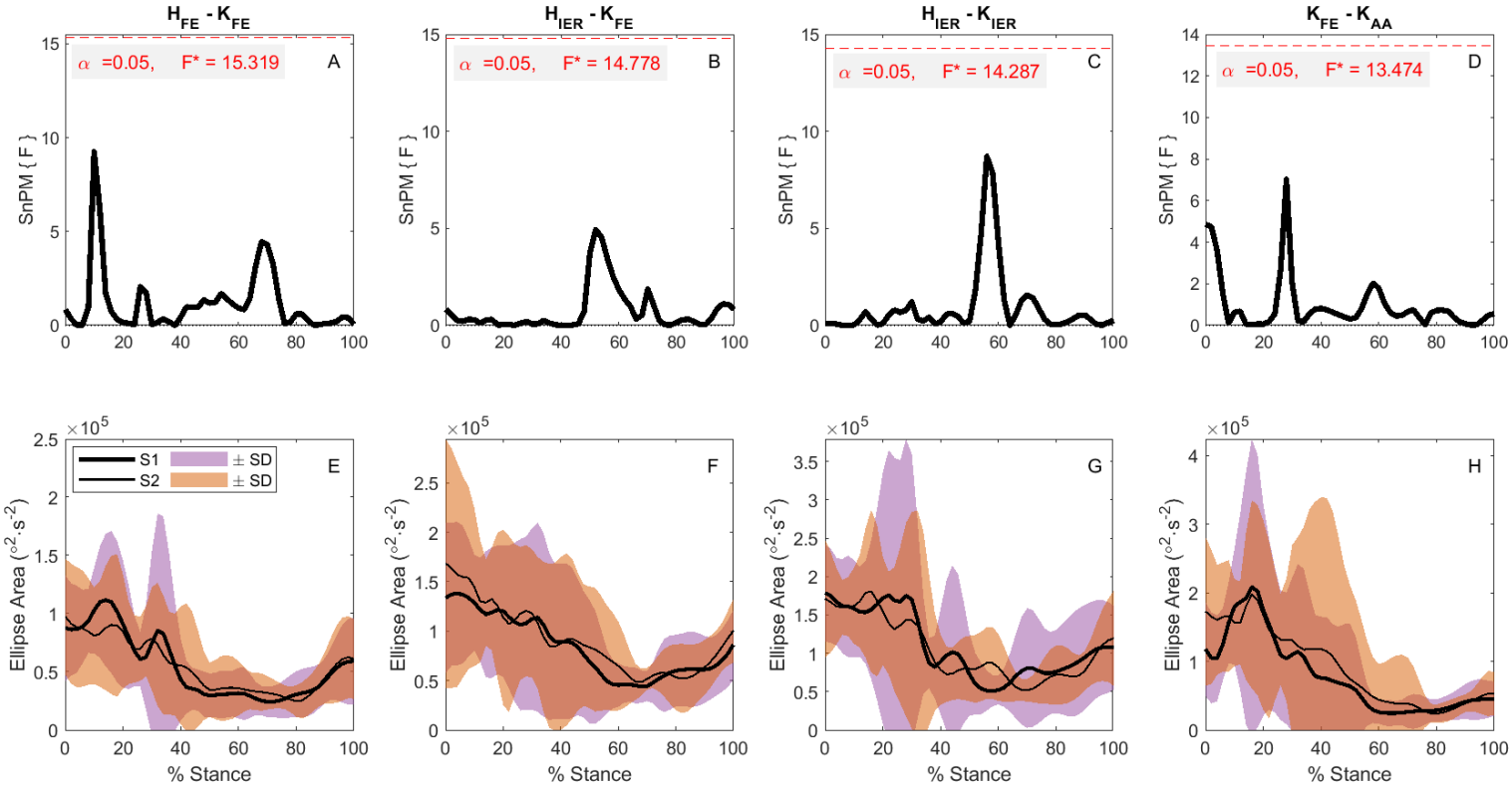


Figure 6.12. SnPM repeated measures ANOVA comparing coordination variability between repeated sessions. The following couplings are reported: A & E) hip flexion/extension – knee flexion/extension, B & F) hip internal/external rotation – knee flexion/extension, C & G) hip internal/external rotation – knee internal/external rotation, D & H) knee flexion/extension – knee ab/adduction. On the top row the black line represents the SnPM(F) statistic and the red dashed line represents the critical value. If the black line crosses the red threshold this represents a statistically significant difference between coordination variability in S1 and S2 of the repeatability study (α = 0.05). On the bottom row the mean and standard deviation of coordination variability across the repeatability participant group is shown.

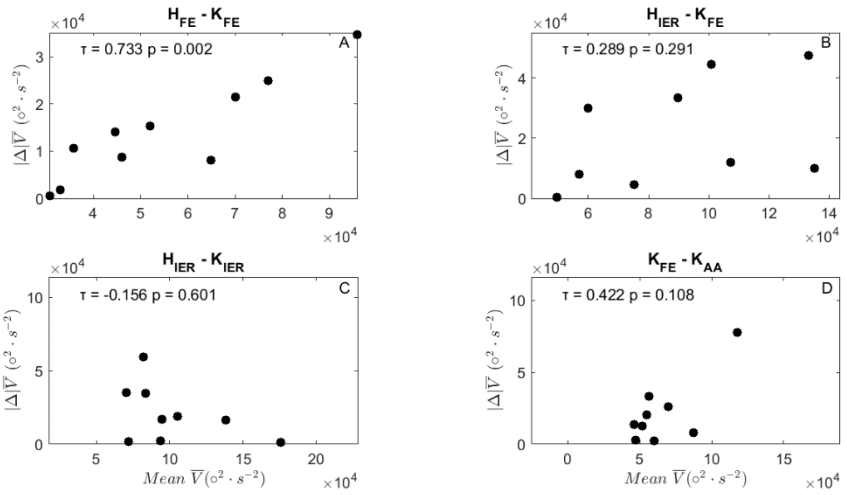


Figure 6.13. Assessment of the scedasticity of mean coordination variability across the stance phase of the cutting movement ($\overline{V}$). Mean $\overline{V}$ across sessions (S1 and S2) is plotted against the absolute difference (|Δ|) in $\overline{V}$ between S1 and S2. The following couplings are reported: A) Hip flexion/extension – knee flexion/extension, B) Hip internal/external rotation – Knee flexion/extension, C) Hip internal/external rotation – knee internal/external rotation, D) Knee flexion/extension – knee ab/adduction. Each point represents a different participant. Kendall rank test results are displayed where τ represents the strength of association and p indicates the significance statistic.

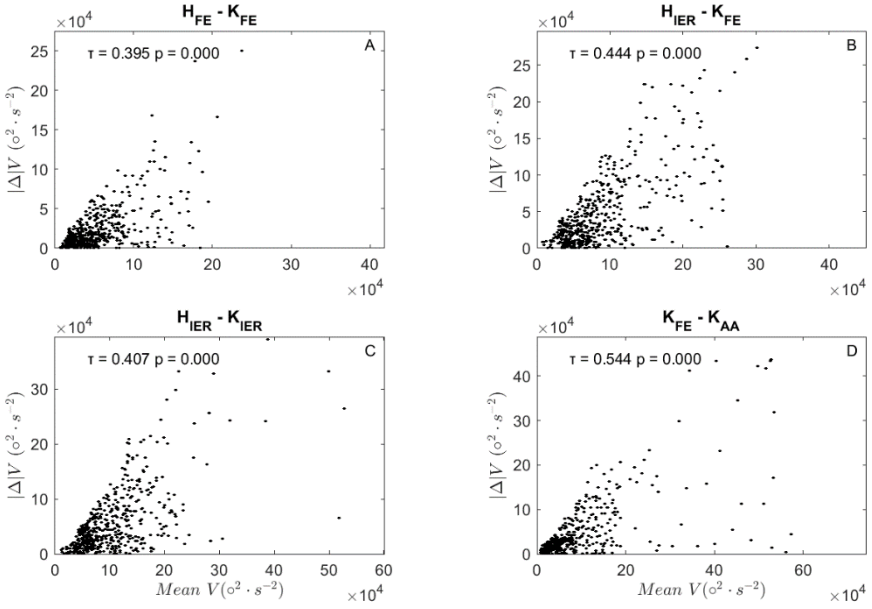


Figure 6.14. Assessment of scedasticity of coordination variability (*V*) at each temporal node of the stance phase of the cut. Mean *V* across sessions (S1 and S2) is plotted against the absolute difference (|Δ|) in *V* between S1 and S2. The following couplings are reported: A) Hip flexion/extension – knee flexion/extension, B) Hip internal/external rotation – Knee flexion/extension, C) Hip internal/external rotation – knee internal/external rotation, D) Knee flexion/extension – knee ab/adduction. There are 51 points represented for each participant: one for every temporal node within the *V* time series. Kendall rank test results are displayed where τ represents the strength of association and p indicates the significance statistic.

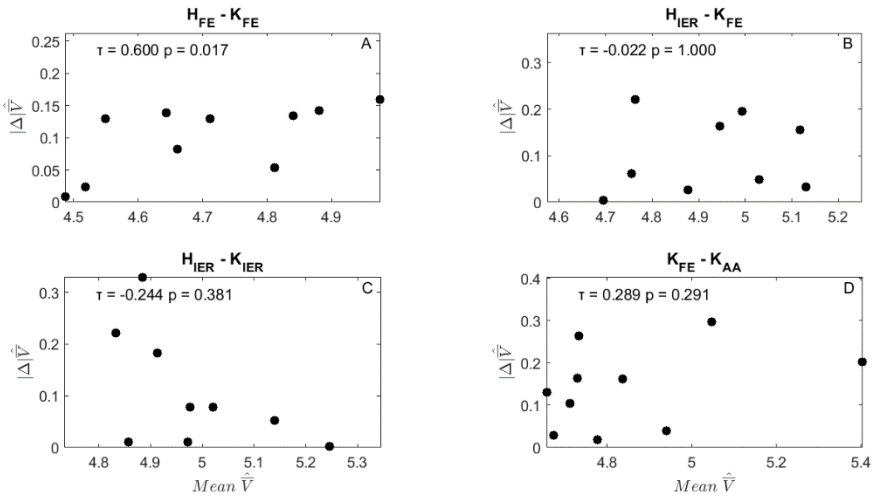


Figure 6.15. Assessment of scedasticity in mean coordination variability across the stance phase of the cutting movement following $\log_{10}$ transform ($\widehat{\bar{V}}$). Mean $\widehat{\bar{V}}$ across sessions (S1 and S2) is plotted against the absolute difference (|Δ|) in $\widehat{\bar{V}}$ between S1 and S2. The following joint angle couplings are reported: A) Hip flexion/extension – knee flexion/extension, B) Hip internal/external rotation – Knee flexion/extension, C) Hip internal/external rotation – knee internal/external rotation, D) Knee flexion/extension – knee ab/adduction. Each point is a different participant. Kendall rank test results are displayed where τ represents the strength of association and p indicates the significance.

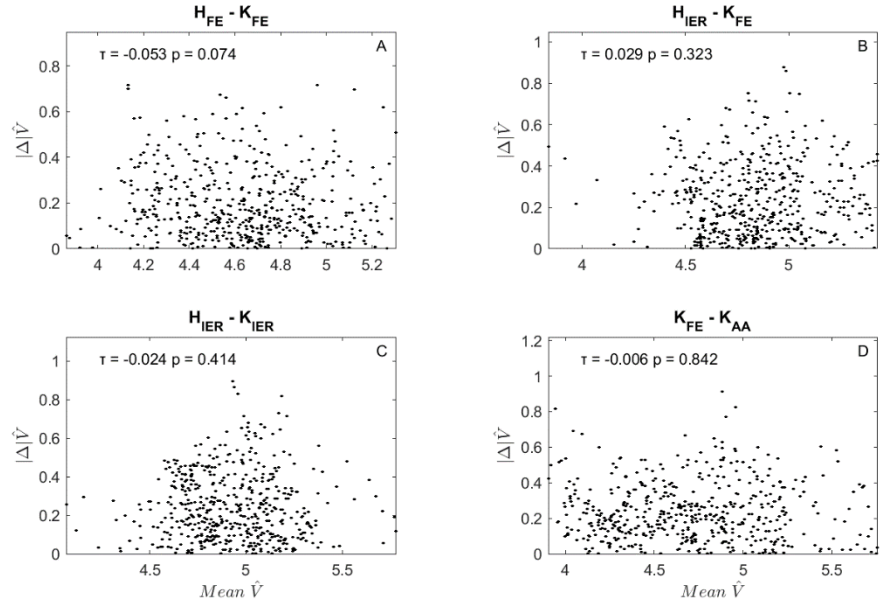


Figure 6.16. Assessment of scedasticity in coordination variability following $\log_{10}$ transform ($\widehat{V}$) at each temporal node. Mean $\widehat{V}$ across sessions (S1 and S2) is plotted against the absolute difference (|Δ|) in $\widehat{V}$ between S1 and S2. The following couplings are reported: A) Hip flexion/extension – knee flexion/extension, B) Hip internal/external rotation – Knee flexion/extension, C) Hip internal/external rotation – knee internal/external rotation, D) Knee flexion/extension – knee ab/adduction. There are 51 points represented for each participant: one for every temporal node within the $\widehat{V}$ time series. Kendall rank test results are displayed where τ represents the strength of association and p indicates the significance statistic.

Mean joint angles

No significant changes were detected between S1 and S2 for hip flexion/extension, hip internal/external rotation or knee flexion/extension. Significant differences were detected at specific time periods during the stance phase for knee ab/adduction at the very end of the stance phase (98-100%, Figure 6.17D) and between 64 and 82% of stance for knee internal/external rotation (Figure 6.17E).

The difference between sessions in joint angles did not appear to be related to the mean joint angle between sessions for any of the five joint angles (Figure 6.18) therefore MDC value time series were calculated for each joint angle variable.

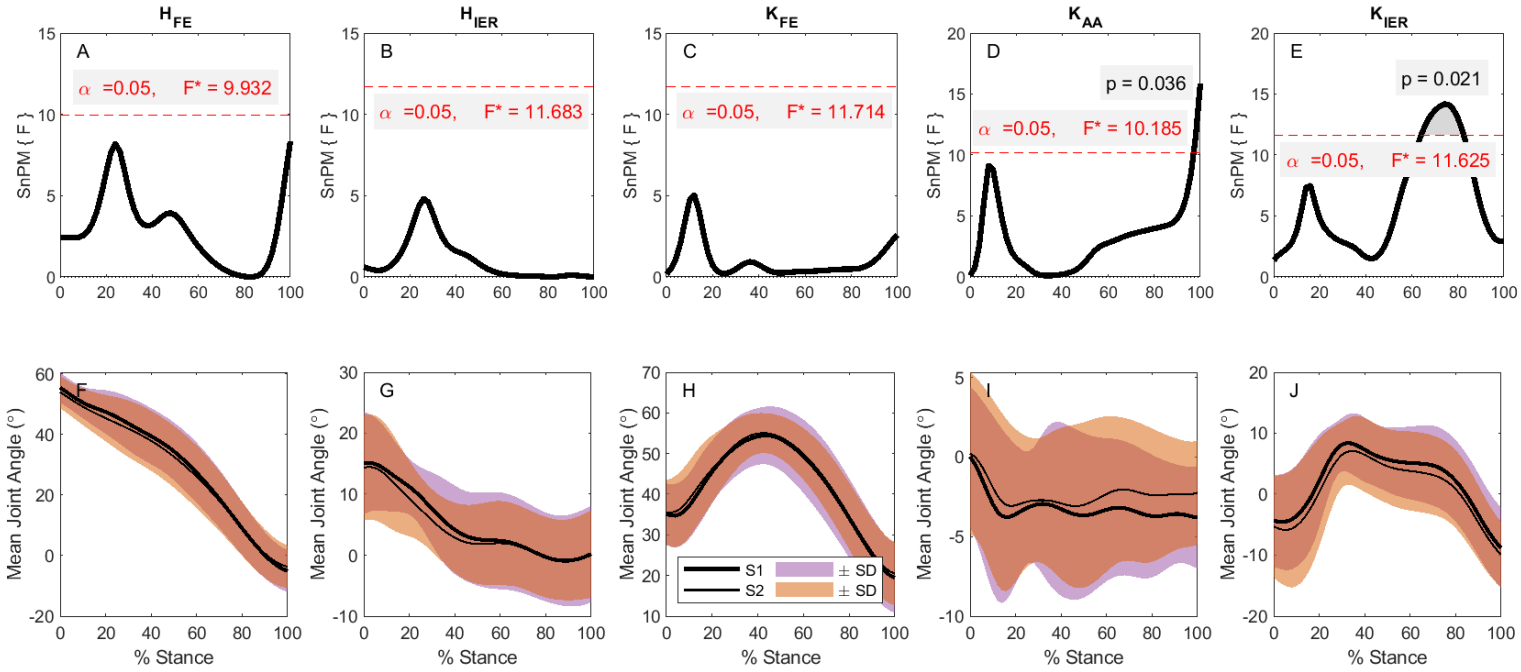


Figure 6.17. SnPM repeated measures ANOVA testing for significant differences in mean joint angles across cycles ($\bar{J}$) between session 1 (S1) and session 2 (S2). The following joint angles are reported: A & F) hip flexion/extension, B & G) hip internal/external rotation, C & H) knee flexion/extension, D & I) knee ab/adduction, E & J) knee internal/external rotation. On the top row the black line represents the SnPM(F) statistic and the red dashed line represents the critical value. If the black line crosses the red threshold this represents a statistically significant difference between the joint angles in S1 and S2 of the repeatability study (α = 0.05). Areas where this has occurred are labelled in grey and the associated p value for the suprathreshold cluster is reported on the figure. On the bottom row the mean and standard deviation of the mean joint angle ($\bar{J}$) across the repeatability study participant group is reported for each session.

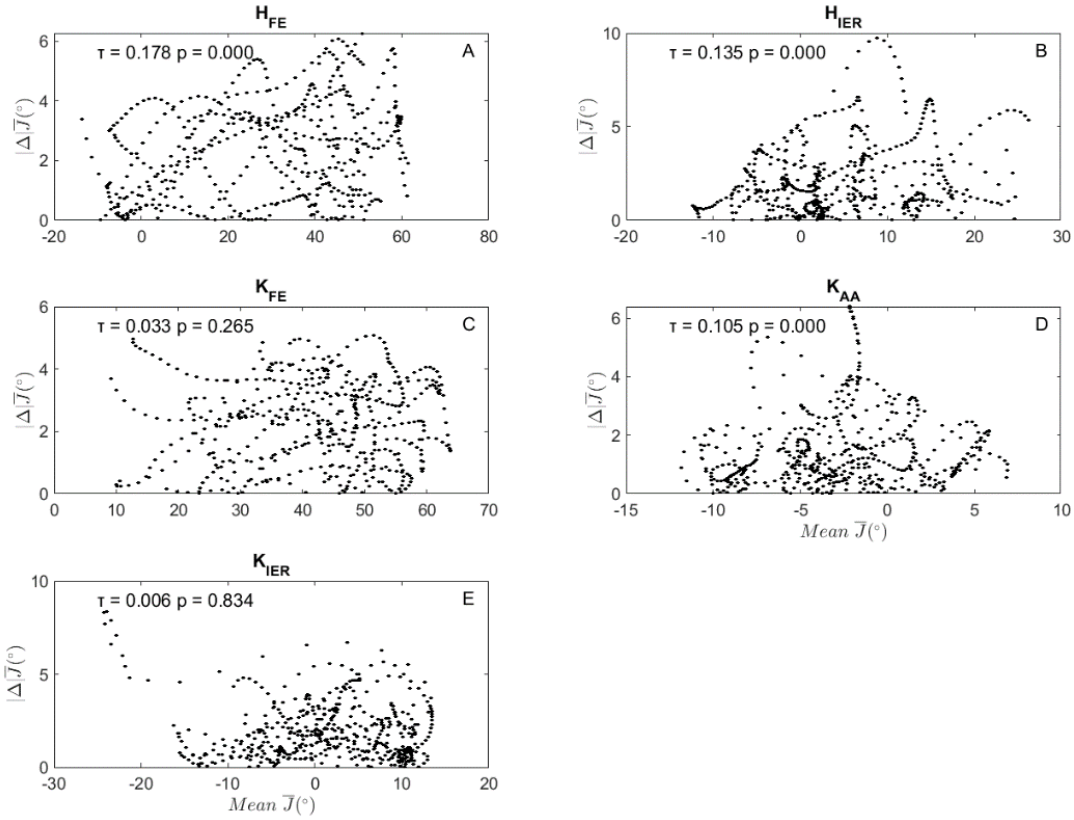


Figure 6.18. Assessment of scedasticity in the mean joint angle across cycles ($\bar{J}$) at each temporal node. Mean $\bar{J}$ across sessions (S1 and S2) is plotted against the absolute difference (|Δ|) in $\bar{J}$ between S1 and S2. The following joint angle couplings are reported: A) Hip flexion/extension B) Hip internal/external rotation C) Knee flexion/extension D) Knee ab/adduction E) Knee internal/external rotation. There are 51 points represented for each participant: one for every temporal node within the $\bar{J}$ time series. Kendall rank test results are displayed where τ represents the strength of association and p indicates the significance statistic.

Minimum Detectable Change

Coordination variability

The MDC ratio for average coordination variability across the gait cycle ($\bar{V}$) was lower for the hip flexion/extension – knee flexion extension coupling than the other three coordination couplings (Table 6.4). The coordination coupling with the highest ratio was hip internal/external rotation – knee flexion/extension rotation (Table 6.4).

When the repeatability of coordination variability for all couplings were considered as time series, the smallest ratio recorded was 1.91 (Figure 6.19D) and the highest was 7.95 (Figure 6.19B). Generally for all coordination variability couplings, the MDC ratio changed considerably throughout the stance phase (ranges: [2.05 to 6.05] for hip flexion/extension –

knee flexion/extension, [2.11 to 7.95] for hip internal/external rotation – knee flexion/extension, [2.00 to 6.64] for hip internal/external rotation – knee internal/external rotation, [1.91 to 5.98] for knee flexion/extension – knee ab/adduction .

Table 6.4. Minimum Detectable Change (MDC) ratios or MDC values for average coordination variability ($\bar{V}$). Different values are reported according to the scedasticity of the data. MDC ratios are reported as ×/÷ and MDC values are reported as ±.

Coupling	MDC
Hip flexion/extension – Knee flexion/extension	×/÷ 1.66
Hip internal/external rotation – knee flexion/extension	×/÷ 2.13
Hip internal/external rotation – knee internal/external rotation	± 88,000 $^{o}\cdot s^{-2}$
Knee flexion/extension – knee ab/adduction	×/÷ 2.14

An example application of the MDC to data collected within this study showed that the absolute values calculated from the MDC ratios varied considerably both throughout the stance phase of the cut and between participants (Figure 6.20).

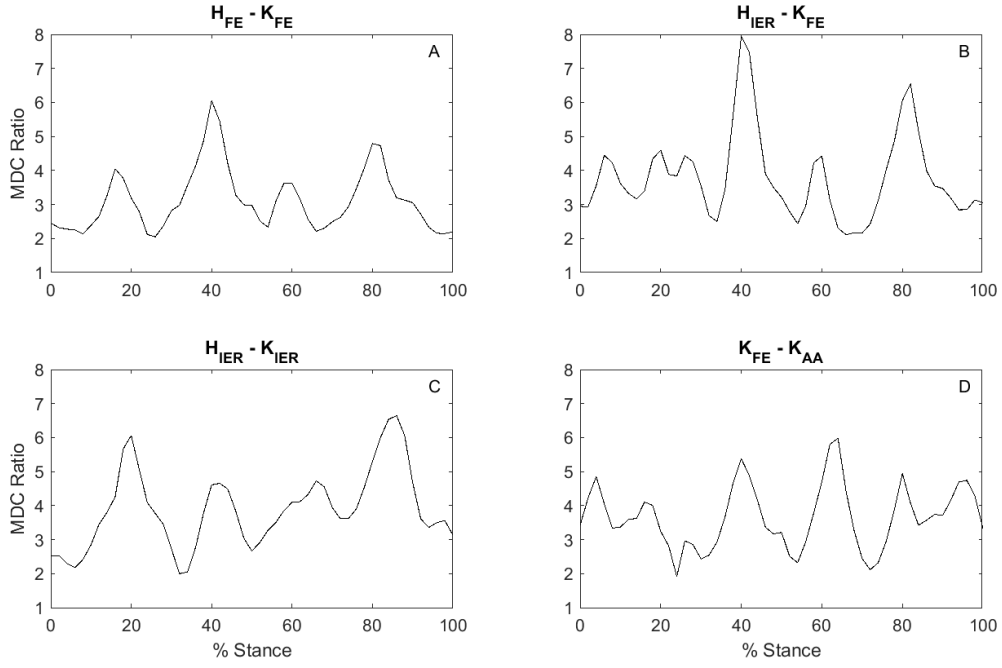


Figure 6.19. Minimum detectable change (MDC) ratios for coordination variability (*V*) across the stance phase of the cutting movement. The following couplings were analysed: A) Hip flexion/extension – knee flexion/extension, B) Hip internal/external rotation – knee flexion-extension, C) Hip internal/external rotation – knee internal/external rotation and D) Knee flexion/extension – knee ab/adduction). The MDC ratios are shown with a solid line and a value of 1 would represent perfect repeatability between sessions. The greater the MDC Ratio, the lower the repeatability is.

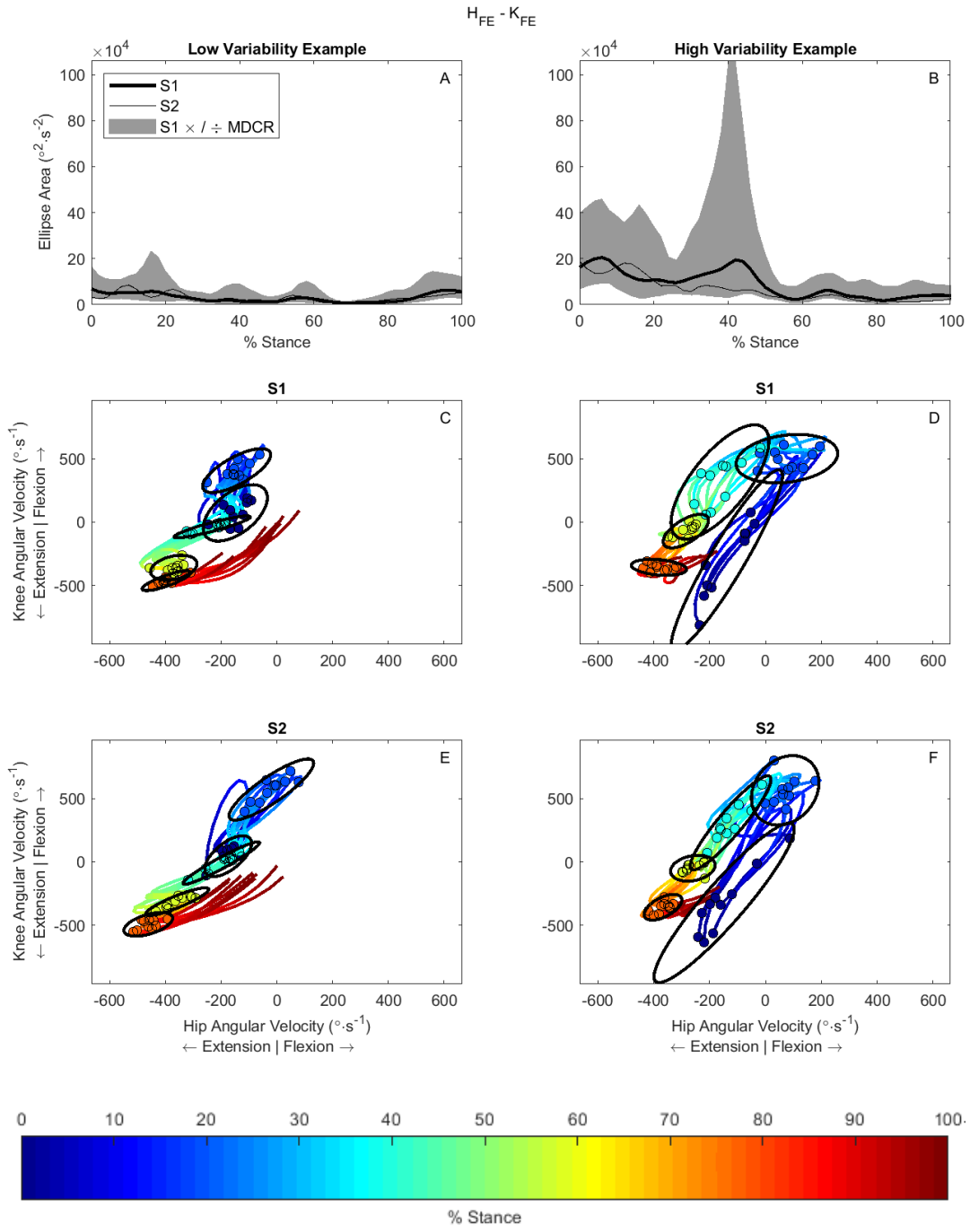


Figure 6.20. Example application of the between day MDC ratio for the participant with the lowest (A) and highest (B) average hip flexion/extension – knee flexion/extension coordination variability in Session 1 (S1). Data from each of the two sessions are plotted: S1±MDC (thick solid line with grey shaded area about it), Session 2 (S2, same day as S1, thin solid line. Example angular velocity – angular velocity plots (C and E) demonstrate the origins of the S1 and S2 data plotted in A for S1 and S2 respectively for the same participant as represented in A. Example angular velocity – angular velocity plots (C and E) demonstrate the origins of the S1 and S2 data plotted in B respectively.

Mean joint angles

Hip flexion/extension had the highest MDC value when averaged across the foot contact and the lowest MDC was observed for knee ab/adduction (Table 6.5). Hip flexion/extension showed consistent MDC values across the first 80% of the stance phase of the cut and

increased repeatability towards the end. Knee flexion/extension appeared consistent in its repeatability across duration of stance (Figure 6.21). Hip internal/external rotation appeared to be least repeatable at the start of stance and become more repeatable towards the end of the stance phase (Figure 6.21B). Knee ab/adduction was more repeatable in the first 40% than the last 60% (Figure 6.21D). The repeated measures ANOVA highlighted a period of significant change between sessions that can be observed at the end of stance where all participants demonstrated a more abducted joint angle. Knee internal/external rotation was less repeatable in the first 40% of stance than in the latter 60% (Figure 6.21E). The repeated measures ANOVA highlighted a period of significant change between 64 and 82 % of stance and it can be observed here that many participants demonstrated a more internally rotated knee in S2 than in S1 during this period. The systematic changes observed in knee ab/adduction and knee internal/external rotation from 98 to 100% of stance and 64 to 82% respectively may affect the validity of the MDC for those variables between those time points.

Table 6.5. Minimum Detectable Change (MDC) of joint angles averaged across the foot contact period.

Joint Angle	Average MDC across the contact phase (°)
Hip flexion/extension	5.3 ± 0.8
Hip internal/external rotation	4.9 ± 1.6
Knee flexion/extension	4.7 ± 0.8
Knee ab/adduction	3.7 ± 0.7
Knee internal /external rotation	4.5 ± 1.3

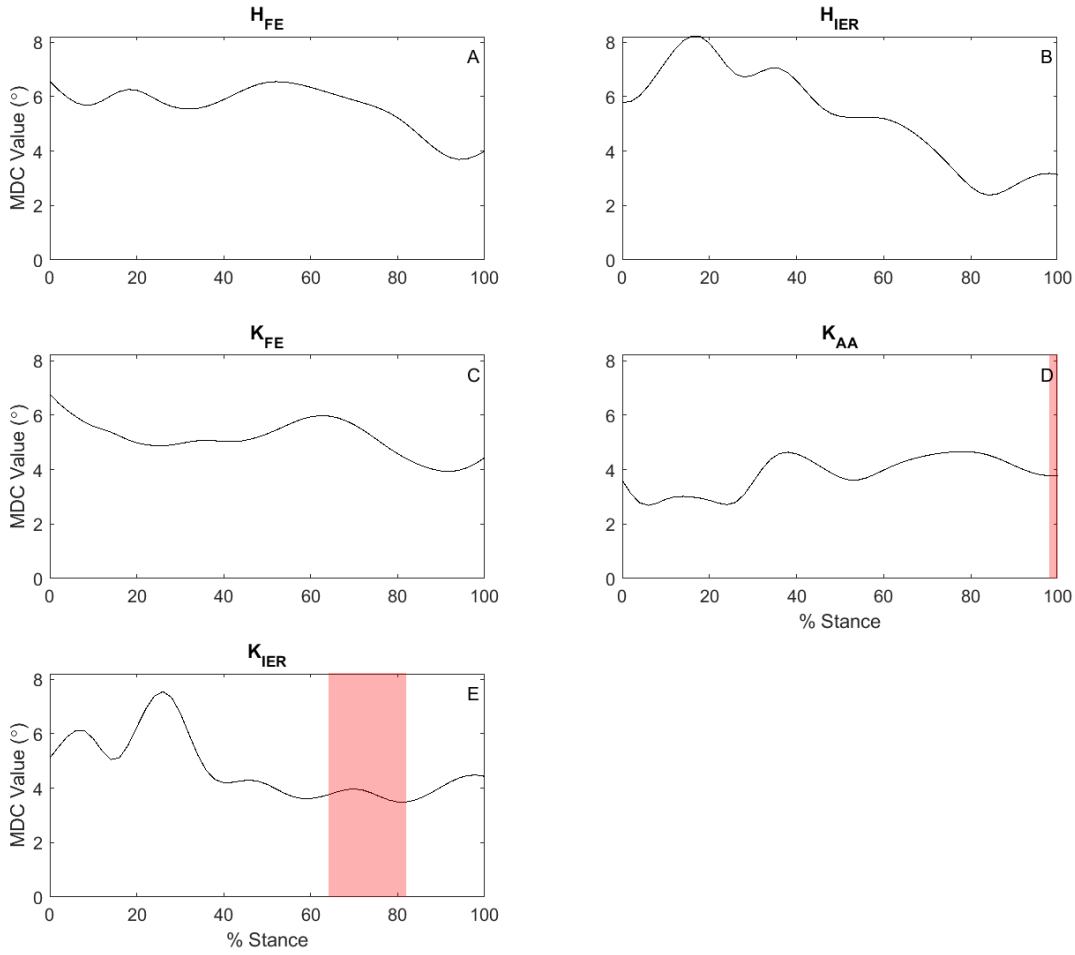


Figure 6.21. Minimum Detectable Change in joint angles across the stance phase of the cutting movement. The joint angles analysed were: A) Hip flexion/extension, H_{FE} B) Hip internal/external rotation, H_{IER} C) Knee flexion/extension, K_{FE} D) Knee ab/adduction, K_{AA} and E) Knee internal/external rotation, K_{IER}. The shaded red areas on plots D and E represent phases of stance within which significant changes were detected in the joint angles between sessions as demonstrated in Figure 6.17 where the MDC values should be used with additional caution.

6.3.2 Fatigue Study

Physiological measures

A SnPM mixed model ANOVA was performed on the heart rate and RPE measurements taken straight after the collection of 24 cutting trials to compare heart rate at F1 (pre-fatigue) compared to F2 (post-fatigue) in the ACLI and ACLR group. A significantly higher heart rate (increase of 23 BPM) and RPE score (increase of 3) was observed after the fatigue protocol at this time point (Table 6.6). Generally, across the duration of data collection an increase in heart rate and RPE was observed from before the cutting movements compared to during and after, heart rate and RPE scores were higher in the post fatigue cuts (F2) than in the pre fatigue

cuts (F1) and the highest heart rates ad RPE scores were observed during the fatigue protocol (Figure 6.22).

Table 6.6. SnPM mixed model ANOVA results ($\alpha = 0.05$) comparing heart rate and RPE. Measurements were taken immediately after the cutting task ended. Effect of group compared ACLI and ACLR participants, fatigue compared the pre and post fatigue conditions and the interaction effect tested whether the response to fatigue differed between the ACLI and ACLR groups. Significant differences ($p < 0.05$) are marked (*).

	Effect of group	Effect of fatigue	Interaction effect
Heart rate post cuts	0.440	<0.001 *	0.439
RPE post cuts	0.281	<0.001 *	0.427

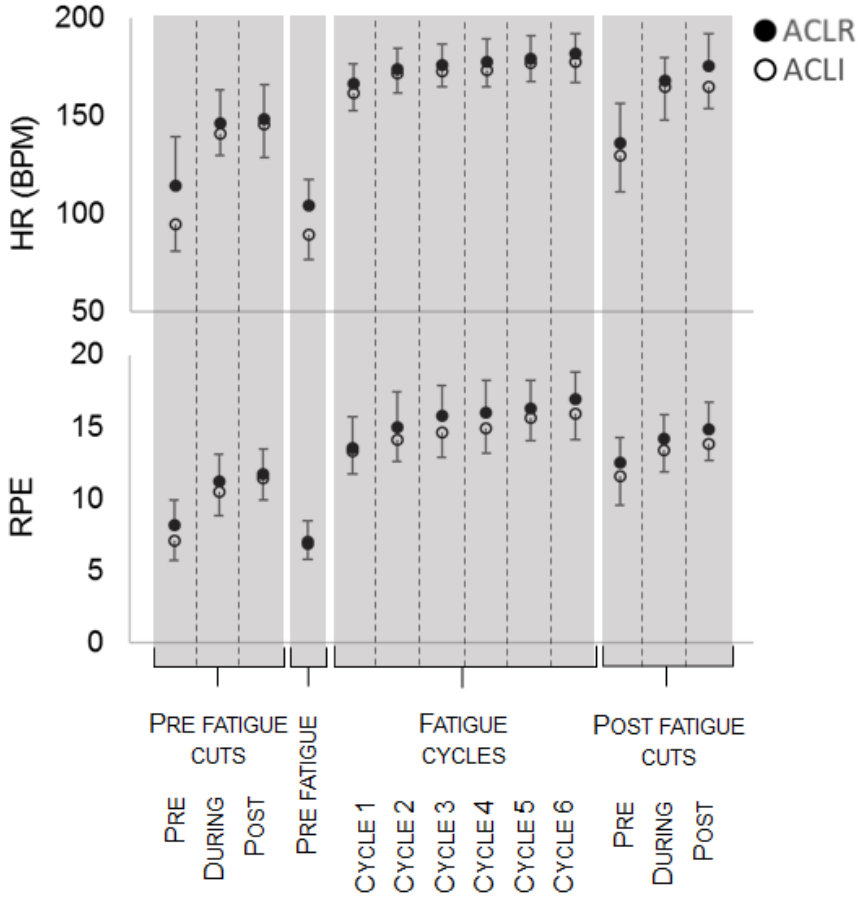


Figure 6.22. Heart rate (HR) and Rating of Perceived Exertion (RPE) of ACLR (filled circles) and ACLI (unfilled circles) groups throughout the different stages of the testing protocol. The standard deviation for each group is indicated by an error bar in one direction from its corresponding data point. The time that each data point was collected corresponds to the heart rate and RPE measurement indicators in Figure 6.1 for the fatigue study components.

Cut performance measures

No systematic changes in cutting performance were observed as a result of the fatigue protocol (Table 6.7). The greatest changes observed in an individual as a result of fatigue were 0.41 $m \cdot s^{-1}$ (increase) for velocity in, 0.41 $m \cdot s^{-1}$ (increase) for velocity out and 8º (increase) for change in direction (Figure 6.23).

Table 6.7. SnPM mixed model ANOVA results (α = 0.05) comparing task performance control measurements. Effect of group compared ACLI and ACLR participants, effect of fatigue compared the pre and post fatigue conditions and the interaction effect tested whether the response to fatigue differed between the ACLI and ACLR groups. Significant differences (p < 0.05) are marked (*).

	Effect of group	Effect of fatigue	Interaction effect
Velocity in	0.315	0.425	0.851
Velocity out	0.316	0.602	0.959
Change in direction	0.511	0.527	0.219

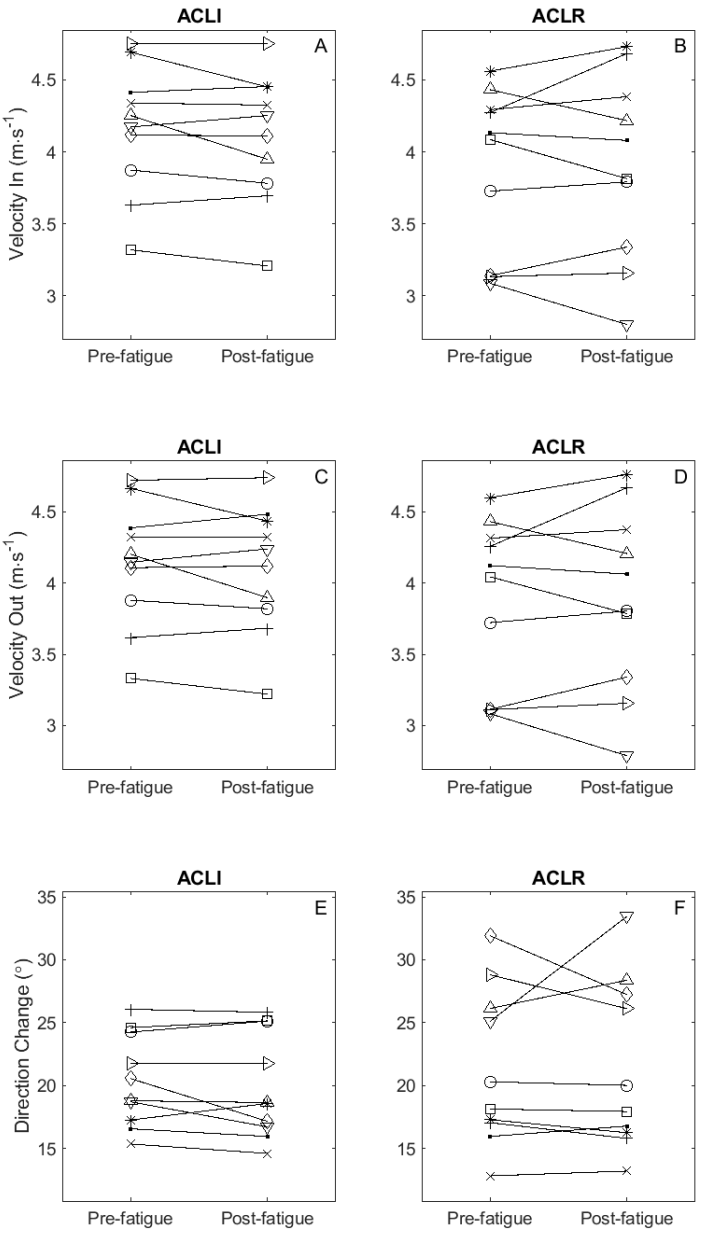


Figure 6.23. Changes in control variables from pre to post fatigue. A and B) Pelvis velocity prior to foot contact C and D) Pelvis velocity after foot contact and E and F) Change of direction from pre-fatigue to post-fatigue for each participant (represented by different markers) within the ACLI (left column) and ACLR (right column) groups.

Coordination variability

No significant differences were detected in the average coordination variability analysis (Table 6.8). There were two examples (Figure 6.24D, Figure 6.27D) where the change in average coordination variability from pre to post fatigue for an individual participant exceeded the minimum detectable change (observed in the same participant in the ACLR group). No changes greater than the MDC were observed for hip internal/external rotation – knee

flexion/extension (Figure 6.25) or hip internal/external rotation – knee internal/external rotation (Figure 6.26).

Table 6.8. SnPM mixed model ANOVA results (α = 0.05) comparing average coordination variability ($\bar{V}$) in the fatigue study. Hip flexion/extension – knee flexion/extension ($H_{FE} – K_{FE}$), hip internal/external rotation – knee flexion/extension ($H_{IER} – K_{FE}$), hip internal/external rotation – knee internal/external rotation ($H_{IER}– K_{IER}$) and knee flexion/extension – knee ab/adduction ($K_{FE} – K_{AA}$). Effect of group compared ACLI and ACLR participants, fatigue compared the pre and post fatigue conditions and the interaction effect tested whether the response to fatigue differed between the ACLI and ACLR groups. Significant differences ($p < 0.05$) are marked (*).

	Group (ACLI v ACLR)	Fatigue (Pre vs Post fatigue)	Interaction effect
$H_{FE} – K_{FE}$	0.787	0.475	0.795
$H_{IER} – K_{FE}$	0.981	0.498	0.991
$H_{IER}– K_{IER}$	0.407	0.936	0.829
$K_{FE} – K_{AA}$	0.737	0.544	0.398

No significant effects were detected in the coordination variability time series for hip flexion/extension – knee flexion/extension or hip internal/external rotation – knee flexion/extension (Figure 6.28 and Figure 6.29). For the hip internal/external rotation – knee internal/external rotation coupling a significant effect was detected for fatigue in that variability was lower in the fatigued condition in the final 4% of stance than before fatigue (Figure 6.30H) but no ACL or interaction effect was observed (Figure 6.30). In the same time period two of the twenty participants had reduced coordination variability by more than the MDC boundaries (Figure 6.30E).

For knee flexion/extension – knee ab/adduction coordination variability a significant effect was observed for ACL group from 4-6% of the stance phase Figure 6.31G). ACLR participants were less variable in this period of stance than the ACLI group (Figure 6.31A & D). No effect of fatigue or interaction effect was observed (Figure 6.31).

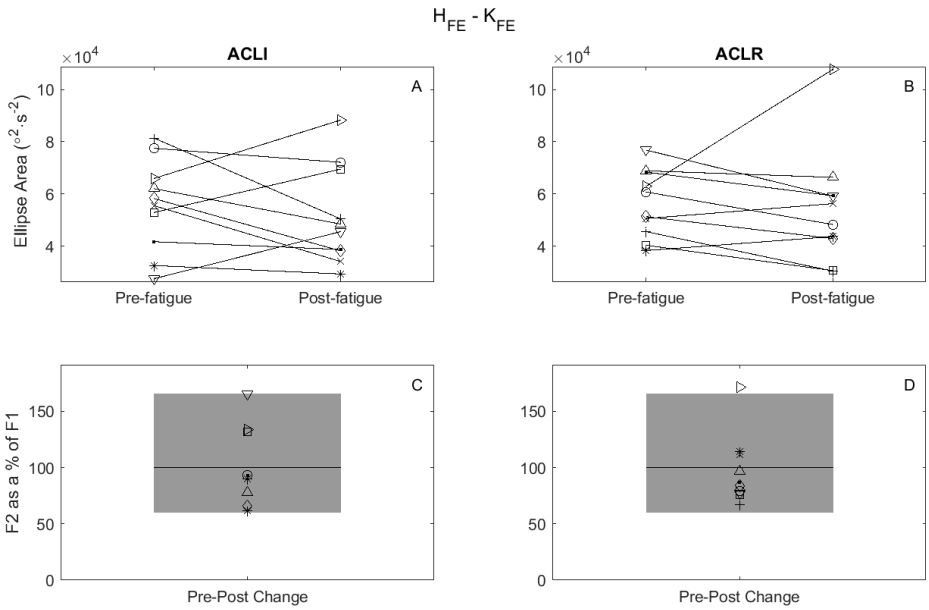


Figure 6.24. Changes in average hip flexion/extension – knee flexion/extension coordination variability in the fatigue study. A and B) Each individual participant in the ACLI (A) and ACLR (B) group are represented by a different marker showing pre fatigue (F1) to post fatigue (F2) changes. C and D) F2 is expressed as a percentage of F1 for each participant in the ACLI (C) and ACLR (D) group and compared to the MDC ratio boundaries (dark grey shading). The line at 1 represents no change between pre and post fatigue. Markers that lie within the shaded area represent where change between pre and post fatigue has not exceeded the MDC and those outside of the shaded areas represent a change in coordination variability greater than the MDC.

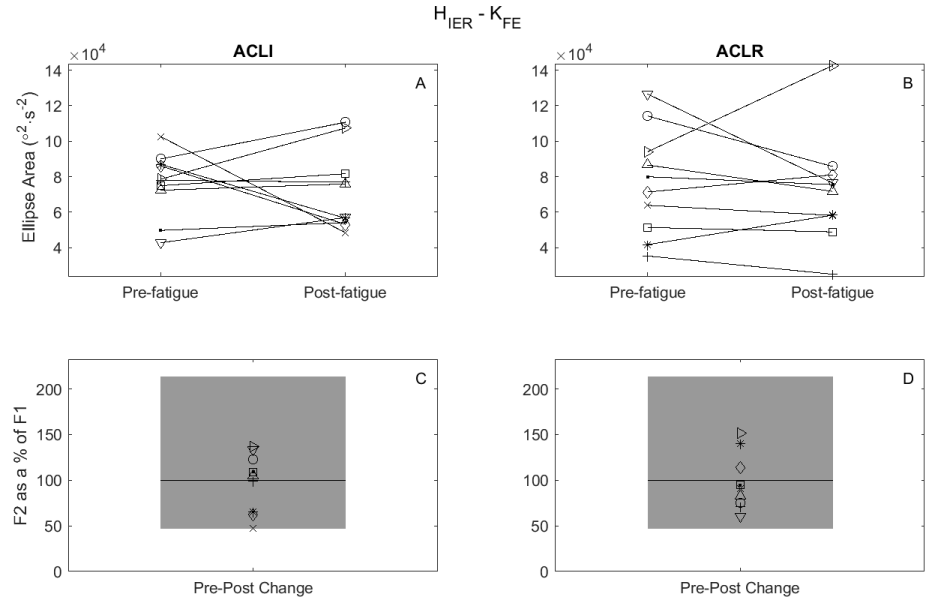


Figure 6.25. Changes in average hip internal/external rotation – knee flexion/extension coordination variability in the fatigue study. A and B) Each individual participant in the ACLI (A) and ACLR (B) group are represented by a different marker showing pre fatigue (F1) to post fatigue (F2) changes. C and D) F2 is expressed as a percentage of F1 for each participant in the ACLI (C) and ACLR (D) group and compared to the MDC ratio boundaries (dark grey shading). The line at 1 represents no change between pre and post fatigue. Markers that lie within the shaded area represent where change between pre and post fatigue has not exceeded the MDC and those outside of the shaded areas represent a change in coordination variability greater than the MDC.

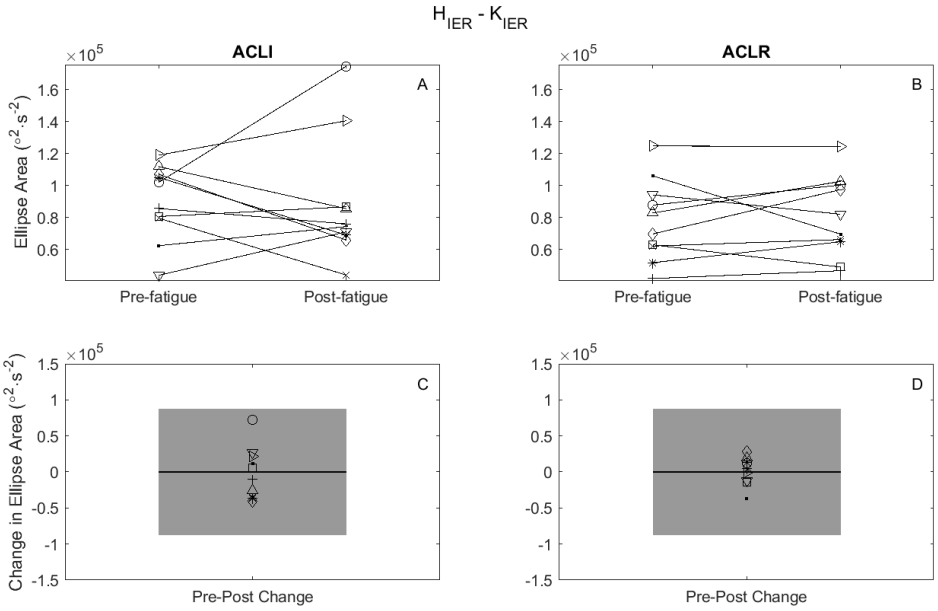


Figure 6.26. Changes in average hip internal/external rotation – knee internal/external rotation coordination variability in the fatigue study. A and B) Each individual participant in the ACLI (A) and ACLR (B) group are represented by a different marker showing pre fatigue (F1) to post fatigue (F2) changes. C and D) The change from F1 to F2 in the ACLI (C) and ACLR (D) group and compared to the absolute MDC boundaries (grey shading). The line at 0 represents no change between pre and post fatigue. Markers that lie within the shaded area represent where change between pre and post fatigue has not exceeded the MDC and those outside of the shaded areas represent a change in coordination variability greater than the MDC.

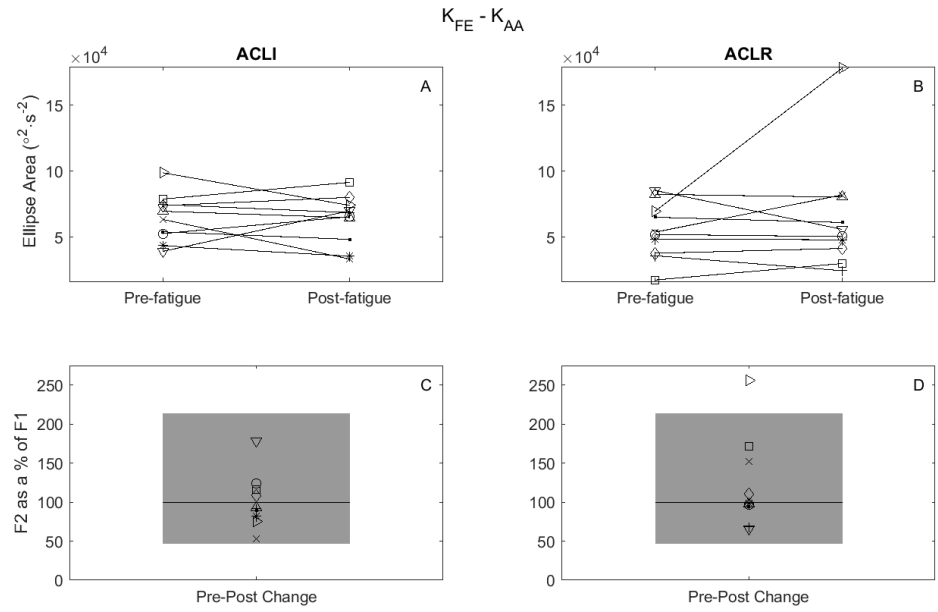


Figure 6.27. Changes in average knee flexion/extension – knee ab/adduction coordination variability for each individual participant in the fatigue study. A and B) Each individual participant in the ACLI (A) and ACLR (B) group are represented by a different marker showing pre fatigue (F1) to post fatigue (F2) changes. C and D) F2 is expressed as a percentage of F1 for each participant in the ACLI (C) and ACLR (D) group and compared to the MDC ratio boundaries (grey shading). The line at 1 represents no change between pre and post fatigue. Markers that lie within the shaded area represent where change between pre and post fatigue has not exceeded the MDC and those outside of the shaded areas represent a change in coordination variability greater than the MDC.

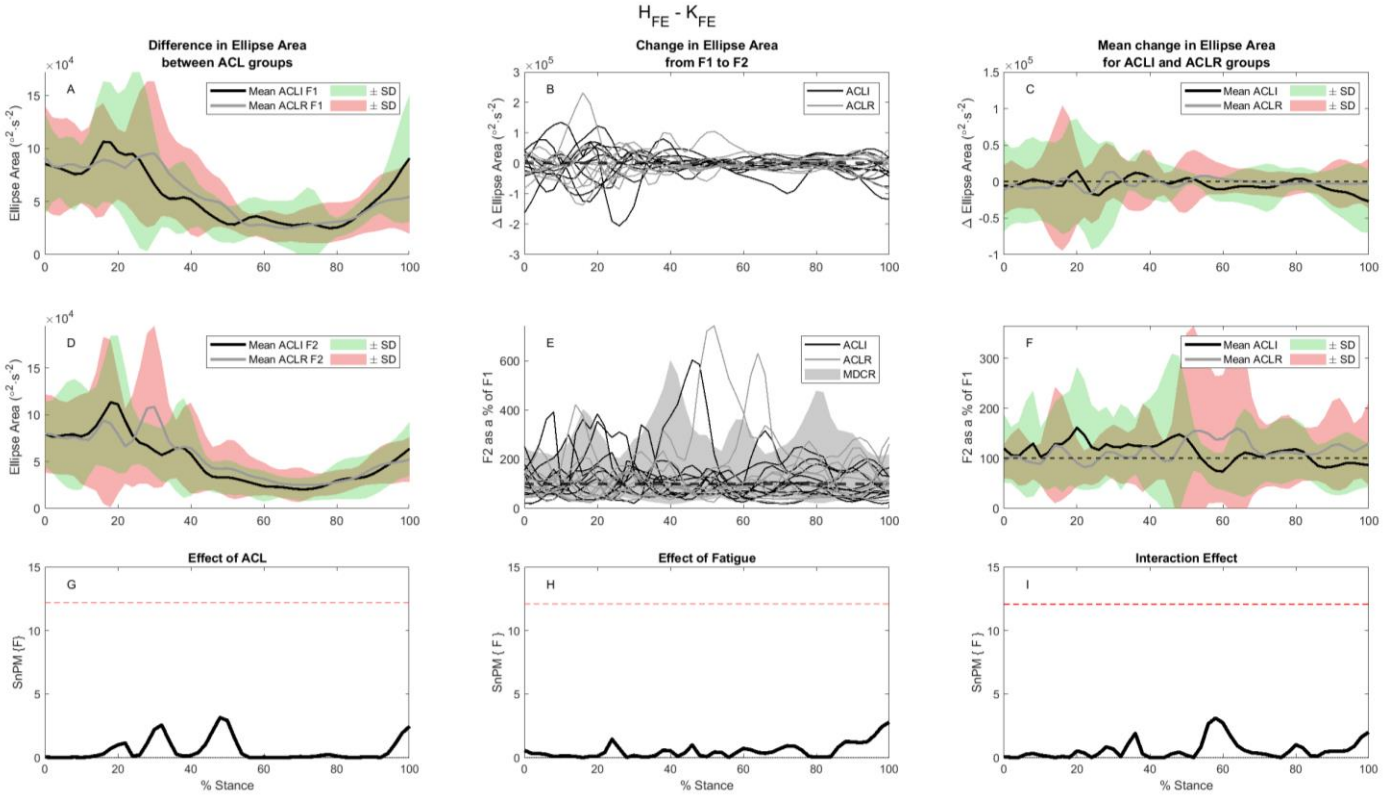


Figure 6.28. Statistical non-Parametric Mapping (SnPM) results of a two-way mixed model ANOVA and supporting data for hip flexion/extension – knee flexion/extension coordination variability. A) Group mean and standard deviations for ACLI and ACLR groups pre fatigue (F1) B) Change in ellipse area between pre and post fatigue for each individual participant C) Group mean and standard deviation of change in coordination variability from pre to post fatigue D) Group mean and standard deviations for ACLI and ACLR groups post fatigue (F2) E) F2 is expressed as a percentage of F1 for each participant and the minimum detectable change ratio is shown with grey shading. Data lines that stray above or below the shaded area represent changes greater than the minimum detectable change. A value of 100 represents no change, a value of less than 100 is a decrease and greater than 100 is an increase in coordination variability. F) Group mean and standard deviation for F2 represented as a percentage of F1. Figures G, H and I shows the SnPM(F) statistic (black line) and the critical value (red dashed line) for the group effect (ACLR vs ACLI), effect of fatigue, and interaction between group and fatigue respectively. The statistically significant difference ($p < 0.05$) is observed when the black line exceeds the threshold of the (red) dashed line.

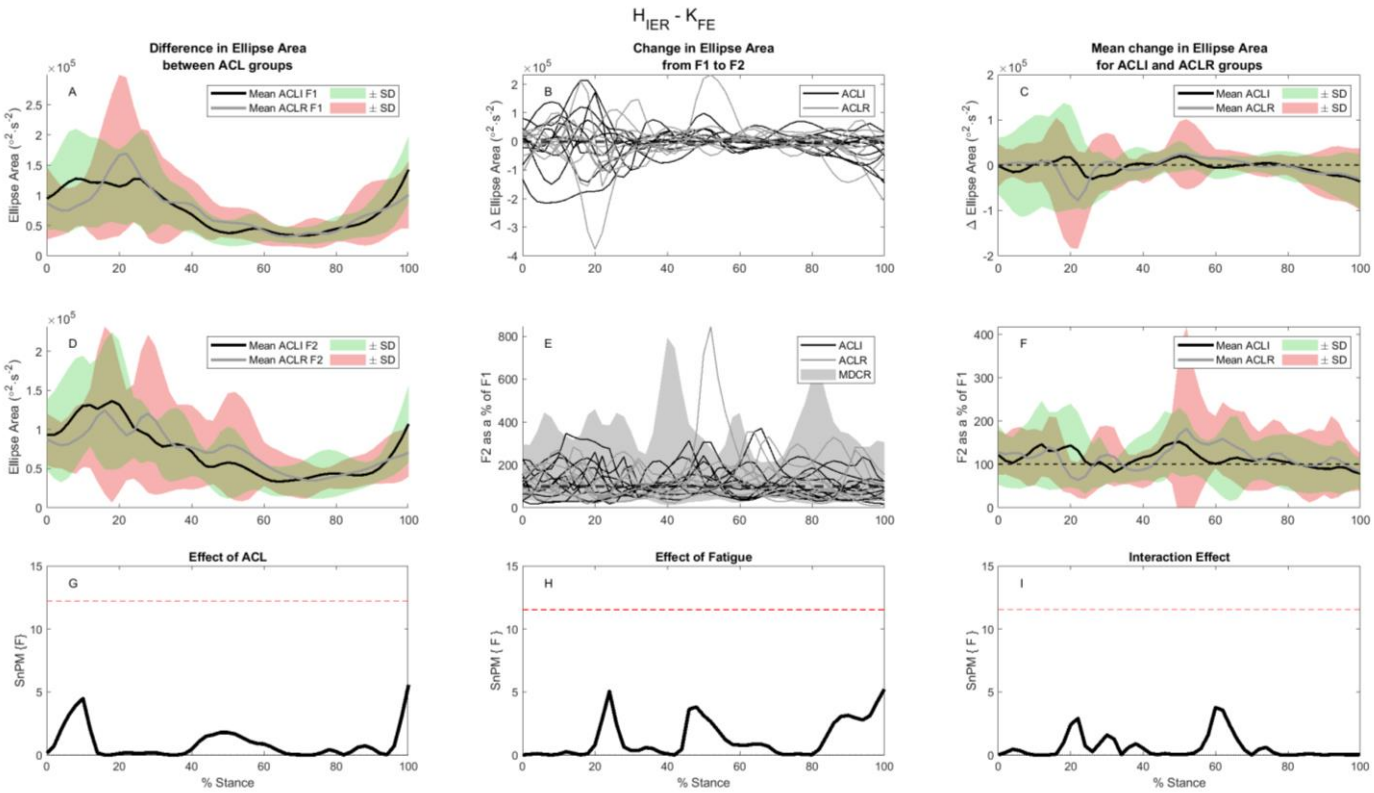


Figure 6.29. Statistical non-Parametric Mapping (SnPM) results of a two-way mixed model ANOVA and supporting data for hip internal/external rotation – knee flexion/extension coordination variability. A) Group mean and standard deviations for ACLI and ACLR groups pre fatigue (F1) B) Change in ellipse area between pre and post fatigue for each individual participant C) Group mean and standard deviation of change in coordination variability from pre to post fatigue D) Group mean and standard deviations for ACLI and ACLR groups post fatigue (F2) E) F2 is expressed as a percentage of F1 for each participant and the minimum detectable change ratio is shown with grey shading. Data lines that stray above or below the shaded area represent changes greater than the minimum detectable change. A value of 100 represents no change, a value of less than 100 is a decrease and greater than 100 is an increase in coordination variability. F) Group mean and standard deviation for F2 represented as a percentage of F1. Figures G, H and I shows the SnPM(F) statistic (black line) and the critical value (red dashed line) for the group effect (ACLR vs ACLI), effect of fatigue, and interaction between group and fatigue respectively. The statistically significant difference ($p < 0.05$) is observed when the black line exceeds the threshold of the (red) dashed line.

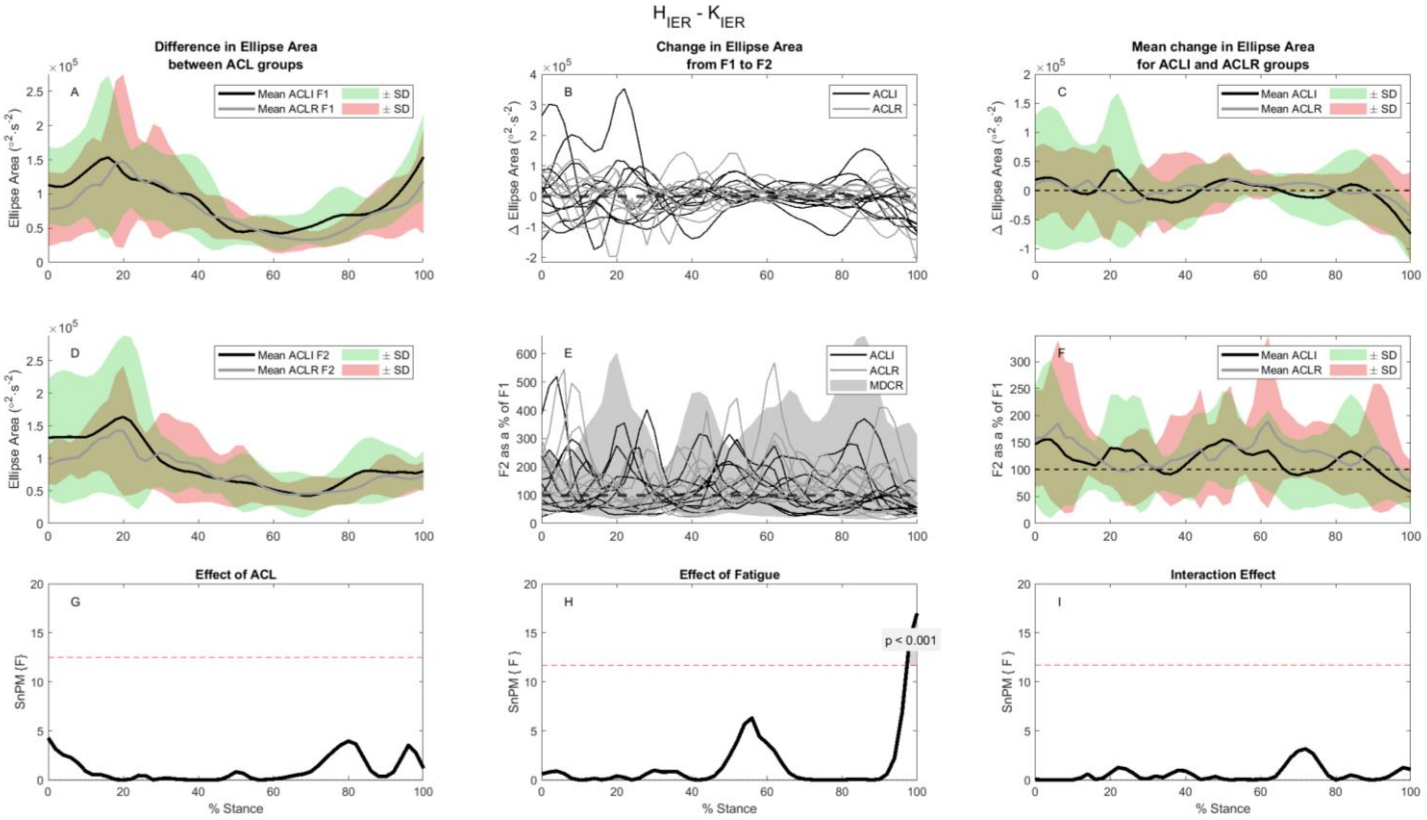


Figure 6.30. Statistical non-Parametric Mapping (SnPM) results of a two-way mixed model ANOVA and supporting data for hip internal/external rotation – knee internal/external rotation coordination variability. A) Group mean and standard deviations for ACLI and ACLR groups pre fatigue (F1) B) Change in ellipse area between pre and post fatigue for each individual participant C) Group mean and standard deviation of change in coordination variability from pre to post fatigue D) Group mean and standard deviations for ACLI and ACLR groups post fatigue (F2) E) F2 is expressed as a percentage of F1 for each participant and the minimum detectable change ratio is shown with grey shading. Data lines that stray above or below the shaded area represent changes greater than the minimum detectable change. A value of 100 represents no change, a value of less than 100 is a decrease and greater than 100 is an increase in coordination variability. F) Group mean and standard deviation for F2 represented as a percentage of F1. Figures G, H and I shows the SnPM(F) statistic (black line) and the critical value (red dashed line) for the group effect (ACLR vs ACLI), effect of fatigue, and interaction between group and fatigue respectively. The statistically significant difference ($p < 0.05$) is observed when the black line exceeds the threshold of the red dashed line.

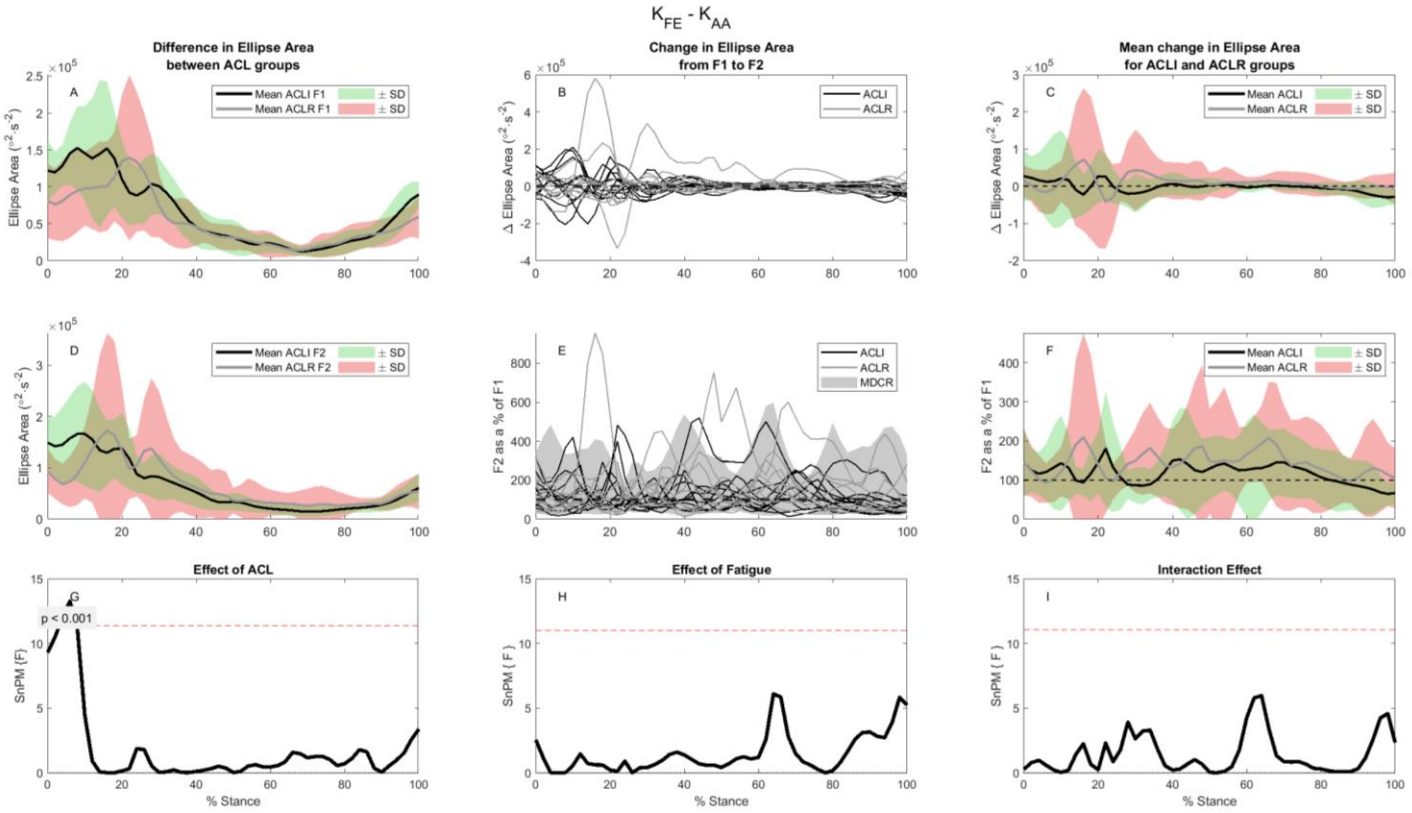


Figure 6.31. Statistical non-Parametric Mapping (SnPM) results of a two-way mixed model ANOVA and supporting data for knee flexion/extension – knee ab/adduction coordination variability. A) Group mean and standard deviations for ACLI and ACLR groups pre fatigue (F1) B) Change in ellipse area from pre and post fatigue for each participant C) Group mean and standard deviation of change in coordination variability from pre to post fatigue D) Group mean and standard deviations for ACLI and ACLR groups post fatigue (F2) E) F2 is expressed as a percentage of F1 for each participant and the minimum detectable change is shown with grey shading. Data lines that stray above or below the shaded area represent changes greater than the minimum detectable change. A value of 100 represents no change, less than 100 is a decrease and greater than 100 is an increase in coordination variability. F) Group mean and standard deviation for F2 represented as a percentage of F1. Figures G, H and I shows the SnPM(F) statistic (black line) and the critical value (red dashed line) for the group effect (ACLR vs ACLI), effect of fatigue, and interaction between group and fatigue respectively. A statistically significant difference ($p < 0.05$) is observed when the black line exceeds the threshold of the red dashed line.

6.4 Discussion

The first aim of this research was to determine the within-day repeatability of coordination variability measured using the velocity ellipse method (VEM) in a cutting movement. Motion capture markers remained in place between testing sessions providing the best possible conditions for reducing measurement error and four different coordination variability couplings were analysed using the VEM for calculating coordination variability: hip flexion/extension – knee flexion/extension, hip rotation – knee flexion/extension, hip rotation – knee rotation and knee flexion/extension – knee ab/adduction. A time series was generated for each coupling variable that indicated how the minimum detectable change (MDC) measure of repeatability varied throughout the duration of and averaged across the period of foot contact. Most of the coordination variability measures were found to be heteroscedastic therefore MDC ratios were calculated to represent the repeatability of these measures. The MDC ratios ranged from 1.66 to 7.95 indicating that the minimum increase between sessions needed to detect a change is between 66 and 695% and the minimum decrease between 40 and 87%. The MDC measures have been used within this research to supplement the interpretation of data on the effect that fatiguing exercise had on coordination variability and also provide a useful reference for understanding whether intra-individual changes in other research are greater than those expected purely due to random fluctuations in the measure.

The second aim of this research was to compare the effect of fatigue between a group of team sports players with ACL reconstructions (ACLR) and those with intact ACLs (ACLI) to understand if coordination variability was different between the two populations, what effect fatigue had on coordination variability, and whether each group had the same of different responses to fatigue. Coordination variability of the hip internal/external rotation – knee internal/external rotation was found to be significantly lower following the fatigue protocol compared to pre fatigue from 96% until the foot left the floor. A between group difference was observed whereby knee flexion/extension – knee ab/adduction variability was significantly lower from 4-6% of stance . Otherwise, no further differences in coordination variability measures were observed that occurred as a result of fatigue or differentiated between the ACLR and ACLI groups.

6.4.1 Repeatability Study

The MDC ratios for coordination variability reported in this chapter for cutting movements were larger than those reported in chapter 4 for running gait, particularly in the time series comparisons (ranges in section 5.3.4 had a maximum value of 4.6 compared to 8.0 reported in this chapter). In section 5.4.1, it was summarised that the MDC ratios were high compared to those observed in other research and that this may mean it would be challenging to observe

changes in coordination variability during running gait that were greater than differences that could be expected due to random fluctuations in the measurement. The MDC ratios observed in this chapter therefore also raise concern for the feasibility of measuring changes in coordination variability using the VEM during cutting movements, so it is important to understand why the MDCs were large.

Whilst there is no parallel comparison to make within the literature regarding the repeatability of coordination variability measures for cutting movements, there is one example of a similar investigation into the repeatability of knee joint angles (Sankey et al., 2015), where the effect of different sessions, testers and biomechanical models were tested. Another study to report repeatability measures across the foot contact period investigated a 90 degree cutting movement (Alenezi et al., 2016). The MDCs reported in this chapter were lower than the two comparison papers (Sankey et al., 2015; Alenezi et al., 2016) for all five joint angle variables by a minimum of 1.0 and maximum of 5.7 (Table 6.9). This may have been because markers remained in place between testing sessions, so error in repeated marker placement was not reflected in the MDCs presented in this chapter. It could also be because a greater number of cuts were measured in this research (10 compared to 4 and 3 in Sankey et al. (2015) Alenezi et al. (2016) respectively) as the number of trials used is thought to influence the stability of a measure (B. Bates, DeVita and Kinoshita, 1983).

Table 6.9. Comparison of repeatability of joint angle data in cutting found in Chapter 6 (mean ± SD across the gait cycle) compared to other research. Standard Error of Measurements reported in other studies have been multiplied by [1.96 * √2] so that all values reported below are MDCs and can be compared.

	Sankey et al. (2015)*	**Alenezi et al. (2016)**	**This Chapter**
Hip flexion/extension	[not reported]	6.90	5.3 ± 0.8
Hip rotation	[not reported]	10.6	4.9 ± 1.6
Knee flexion/extension	8.9	5.7	4.7 ± 0.8
Knee ab/adduction	4.7	4.8	3.7 ± 0.7
Knee rotation	8.3	7.5	4.5 ± 1.3

***N.B. average values for the duration of foot contact were estimated by eye from graphs within the article. and the most repeatable observer's data was used of the two observers that were presented.**

Given that the methods in this chapter provided a best case scenario for reducing measurement error (markers remained in place) and the MDC in joint angles were similar or improved upon those reported elsewhere, the high MDCs found for coordination variability in this chapter do not appear to be specific to this dataset and are therefore important to be aware of for data collected in other laboratories.

Within the context of this thesis, the MDC ratios observed for cutting were much greater than those reported in chapter 5.3.4 for running gait. Two possible contributing factors to this observation that may interact with one another is that fewer trials were used to calculate coordination variability in the cutting task than in gait and that the variability observed in cutting was also higher than in gait. When fewer trials are used, each individual trial holds a greater weighting on outcome measures and therefore on the calculated ellipse area. Thus, single examples of variation in performance are likely to have a greater effect on the outcome. The angular velocity - angular velocity plots for hip flexion/extension – knee flexion/extension have been repeated (Figure 6.32) alongside those measured for gait in Chapter 5 (Figure 6.33). The 'high example' from cutting demonstrated just how large the ellipse became when one data point was positioned differently to the rest (blue points, 20% of gait cycle, single blue point at approximately -300,0). To date there have been no investigations around the number of cutting trials needed for any measure of coordination variability to stabilise. Other research has used between four (Pollard et al., 2015) and seven (Pollard et al., 2005; Pollard et al., 2015; Weir et al., 2019) cutting trials. Thus, this research presented the highest number of trials from which cutting coordination variability has been calculated but it is possible that even with ten trials, coordination variability might not converge to a stable value. The contraposition is that there are challenges associated with collecting a large number of trials, which may themselves impact the validity of the data such as maintaining a consistent level of motivation and fatigue and further research would be necessary to determine the number of trials necessary for values to stabilise without observing a systematic change due to factors such as motivation or fatigue.

The greater variability generally observed in cutting compared to gait, could be a result of the number of performance factors that could vary in the cut compared to in gait where the treadmill was set to a constant velocity. No significant changes were observed between sessions but individual participants varied in their performance of the cutting task (velocity in, velocity out and changes of direction) both within and between sessions (Figure 6.11). Variability in performance has been suggested as a positive performance feature of cutting (Weir et al., 2019) but is likely to also increase the coordinative variability measured within a session. The increased variation in cutting combined with the reduced number of trials may reduce the repeatability of coordination variability in the cutting task as fewer samples (repeated cutting trials) are taken from a broader distribution of values. This would lead to a greater probability of sampling error.

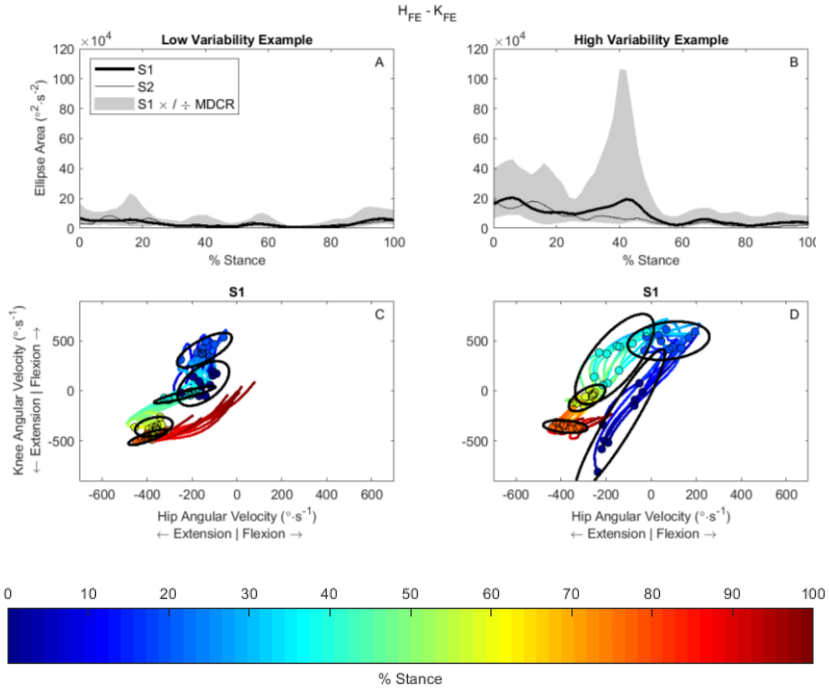


Figure 6.32. Repeat of Figure 6.20 demonstrating hip flexion/extension – knee flexion extension coordination variability during cutting for the participant in the repeatability study with the lowest (A & C) and highest coordination (B & D) variability in session 1 (S1). Plots A and B show coordination variability plotted against time and plots C and D show the corresponding angular velocity – angular velocity plots with example ellipse areas shown at 0, 20, 40, 60, 80 & of stance. N.B. the scale of the y axis on A and B is ten times greater than in Figure 6.33.

Figure 6.33. Repeat of Figure 5.17 demonstrating hip flexion/extension – knee flexion extension coordination variability during running gait for the participant in the repeatability study with the lowest (A & C) and highest coordination (B & D) variability in session 1 (S1). Plots B and C show coordination variability plotted against time and plots C and D show the corresponding angular velocity – angular velocity plots with example ellipse areas shown at 0, 20, 40, 60, 80 & of the gait cycle. N.B. the scale on A and B is ten times smaller than in Figure 6.32

Finally, the MDC time series analysis was included to identify whether variability changed during different phases of the movement, but there was no discernible pattern in how the MDC changed throughout the stance phase of the cut. Instead, the MDC ratio appeared to oscillate, in a similar fashion to that which was observed in Chapter 5. In previous research into coordination variability in cutting Pollard et al. (2005) and Weir et al. (2019) have performed their analyses based on linear time normalisation of the stance phase. Samaan et al. (2015a) however identified two features in the vertical ground reaction force (peak force and a trough in force following the peak) which they used to investigate individual phases within the stance phase. More research would be required to determine whether piecewise temporal normalisation techniques might reduce some of the within and between person variability in timing, thereby reducing coordination variability overall. It is possible that a reduction in total variability might increase the repeatability of the coordination variability measure via a reduction in sampling error but it would also artificially remove some of the temporal variability in the analysis process. The researcher would have to judge whether this is appropriate for the research question they are asking.

6.4.2 Fatigue Study

Coordination variability

Effect of group

No significant differences were observed for average coordination variability across the stance phase between the ACLI and ACLR groups, nor for the majority of coordination variability time series comparisons. Knee flexion/extension – knee ab/adduction coordination variability was found to be significantly lower in the ACLR groups from 4-6% of foot contact ($p = 0.001$) compared to ACLI (Figure 6.31G). The data from this study cannot explain the causative reasons for this difference, but speculatively, lower knee flexion/extension – knee ab/adduction variability in the ACLR group could be an effect of the ACL injury and reconstruction, or it could also have been one of multiple factors that made those individuals susceptible to ACL injury in the first instance. The evidence in support of this is however limited and further research would be required to understand why low knee flexion extension – knee ab/adduction variability might either occur as a result of injury or be related to increased risk of injury. The lower knee flexion-extension – knee ab/adduction variability observed in this chapter does not mirror the findings of Pollard et al. (2015), where variability was significantly higher in the ACLR group compared to the control population for knee flexion/extension – knee ab/adduction and three other joint couplings where coordination variability had been averaged across the first 40% of stance. It is possible that different methods used to calculate coordination variability may have been responsible for these

differences. Pollard et al. (2015) calculated coordination variability using the method first proposed by Heiderscheit, Hamill and van Emmerik (2002) that relies on circular statistics and can therefore be affected by steep rises in coordination variability when the vectors joining consecutive points on the angle – angle plot are short, and uses the change in joint angle about a single axis of rotation as an input to its calculations. In comparison, the velocity ellipse method used in this chapter is not affected by the length of the vector connecting consecutive data points on the angle – angle plot, and uses angular velocities as an input therefore some differences as a result of different analysis methods can be expected.

Effect of fatigue

The fatiguing exercise combined with the increased intensity of the post-fatigue cuts elicited an average increase in HR (23 BPM) and RPE (3 points on the RPE Scale, Figure 6.22) that was confirmed as statistically significant when the final time points form the pre and post cut measures were compared. Before the post-fatigue cut data were collected, the participants had already completed a minimum of 24 maximum intensity cuts and drop cuts, 30 drop jumps and 60 maximum intensity change of direction tasks. The research that informed the fatigue protocol content (Davidson and Trewartha, 2008) supported that the demands placed on the participants within this chapter were comparable with those faced by netball players within the first quarter of a match but condensed into a shorter period of time.

Decreased coordination variability was hypothesised in the fatigued condition compared to pre-fatigue but no significant changes were detected in average variability across the stance phase of the cut as a result of the fatigue protocol. In the coordination variability time series data, a significant decrease was observed in hip internal/external rotation – knee internal/external rotation coordination variability for the last 4% of the stance phase in the fatigued condition. This provided an example of where the time series analysis provided additional detail that was not detected by averaging coordination variability over the entire stance phase. When the percentage changes from pre to post fatigue were compared to the lower boundary of the MDC only 2 of the participants had reduced their coordination variability for hip internal/external rotation – knee internal/external rotation by an amount greater than the MDC within the period of statistical significance. Thus there is potential that certain areas of the knee were more repetitively loaded under fatigue which could have implications for future injury if the repetitive nature of hip internal/external rotation – knee internal/external rotation led to a decrease in the structural integrity of the ACL (Wojtys, Beaulieu and Ashton-Miller, 2016), but the magnitude of change observed in each individual was mostly too small to have been meaningful as it did not exceed the minimum detectable change for them.

Samaan et al. (2015a) measured coordination variability using the same method as in Tepavac and Field-Fote (2001) prior to and following an isolated hamstring fatiguing protocol and found hip rotation – knee rotation coordination variability in the impact and weight acceptance phases was lower in the fatigued state. The authors suggested that the reduction in variability might limit the capacity to adapt to environmental perturbations as movement patterns were less flexible during the period when ACL injury is known to occur (early in the stance phase). In this chapter, lower hip rotation – knee rotation variability was also detected but in a different period of the movement (the final stages of push off). Although Samaan et al. (2015a) did not statistically test the latter stages of the movement, they did report graphs of coordination variability which did not indicate an obvious difference at the end of the contact phase. Thus the lower variability in the early stages of the stance phase observed by Samaan et al. (2015a) was not observed in the data collected in this chapter, as lower variability was only observed at the end of the movement. Samaan et al. (2015a) specifically fatigued the hamstring and also calculated coordination variability using the method first presented by Tepavac and Field-Fote (2001) whereas in this chapter fatigue was induced via more functional exercise protocols and coordination variability was calculated using a technique that is not affected by the length of vectors on the angle – angle plot, and uses angular velocities as inputs. These differences in methods and analysis could explain why the same changes were not observed in this chapter as in Samaan et al. (2015a).

Interaction between group and fatigue

No significant interaction effects were detected for the variability of any of the four coordination couplings as averaged or time series measures. This suggested that changes in coordination variability due to the fatigue stimulus were similar between the ACLR and ACLI group. Previous research has not investigated whether coordination variability has a different response to a fatigue stimulus in ACLR compared to ACLI so this finding cannot be compared with other research. The average time since ACL reconstruction in the ACLR population in this chapter was 5 years and the population were actively participating in sports, in many cases to a very high level and had not sustained a second ACL injury in those years at the time of testing. This may also be a relevant factor for explaining why very few between group differences were detected in this chapter. Overall the general absence of large differences in coordination variability group and interaction differences could imply that in the best case scenarios, ACL reconstruction may either not have a large effect on coordination variability, or that these differences can be addressed with rehabilitation programmes over time.

6.4.3 Limitations

Coordination variability requires the collection of multiple movement trials across which variability is calculated. The cut manoeuvre is a task which when performed in team sports is inherently variable due to interactions with your own team and the need to stay with (mark) or break free from opposition. In order to measure coordination variability for this chapter and other research (Pollard et al., 2005; Pollard et al., 2015; Samaan et al., 2015a; Weir et al., 2019) the task was constrained to within a set path, with a fixed distance over which to accelerate and the focus of attention was on the task itself (as opposed to another player or a ball). An important next step to understand whether the results obtained in the constrained laboratory task are relevant to repetitive loading would be to understand if the same individuals that show high or low variability in the lab are variable in training and competitive environments too.

Ten participants is not unusually low for a repeatability study in cutting biomechanics compared to other published research: e.g. Sankey et al. (2015) had eight participants, Alenezi et al. (2016) had fifteen. The consequence of conducting research with relatively small samples such as these is that there is a higher likelihood that the sample of data did not provide a true representation of the population. It is not known if the MDC would stay the same, be lower or higher if the number of participants had been greater, but the possibility that it might change should be considered when interpreting the MDC observed in this research. The participants in the fatigue study however were competing in team sports that involved change of direction movements at high levels and therefore it was important to use as similar a group of athletes in the repeatability study as possible and it was therefore challenging to recruit larger (20-50) numbers of participants as have been recommended for repeatability studies (Hopkins, 2000; Atkinson and Nevill, 2001). Sample size may also have been a limiting factor in the fatigue study. One possible consequence of too small a sample size is that the alternative hypothesis may incorrectly be rejected (K. Button et al., 2013). One of the strengths of this chapter and Chapter 5 was the investigation of the MDC as part of the repeatability study to understand what magnitude of change might represent more than random fluctuations in repeated measurements. Significance testing does not account for the magnitude of differences observed between groups or as a result of an intervention, and this has been highlighted as a limitation (Greenland et al., 2016). Using the MDC value for the one coupling measure that was homoscedastic (average hip internal/external rotation – knee internal/external rotation) a change of 88,000$^{o2}\cdot s^{-2}$ would be needed to suggest that the change observed was greater than would be observed due to random fluctuations in the measurement. The standard deviation of the fatigue study participants' average hip internal/external rotation – knee internal/external rotation was 24,700$^{o2}\cdot s^{-2}$ (both ACLI and ACLR groups prior to fatigue combined), therefore

the true effect size that would be required for the change to be considered greater than pure fluctuation would be 1.89 (calculated in GPower from variances, $\alpha = 0.05$, power = 0.8, Faul et al. (2007)). An effect size of 1.89 is large (Hopkins et al., 2009) and further emphasises how low repeatability (i.e. high MDCS) of the coordination measures could restrict the ability to detect meaningful differences and changes in coordination variability. The repeatability of coordination variability measures is therefore a greater concern for limiting the ability to detect group differences and changes in coordination variability than the sample size of the fatigue study.

For the purpose of applying the MDC to the fatigue study data, it would have also been beneficial to use the same population in both studies. Unfortunately, this was not possible: the most elite participants were no longer available to participate, and the repeatability study data collection was conducted after the fatigue study. Thus, using the same population would have resulted in different limitations related to increased familiarity of the task in the repeatability study compared to the fatigue study. Consequently, a population of female team sports players was convenience sampled for the repeatability study, but the performance level was lower than that of the participants recruited in the fatigue study. There is currently no evidence to support or refute that the repeatability of coordination variability in cutting might be different between an elite population compared to those playing competitively but at a lower level. Not every piece of research is able to collect extensive repeatability information on the same population as they conduct their applied research and groups are believed to be similar enough that the MDCs from the repeatability study still provide useful information for the interpretation of data for other competitive female team sports players.

In this chapter variability in task performance was monitored by measuring aspects related to the velocity of the pelvis segment prior to and following the stance phase of the cut and the change in the direction of travel of the pelvis segment prior to and following the stance phase of the cut. No significant group changes were detected either in the repeatability or fatigue study participants. It would be interesting to further analyse task performance data separately for each participant to understand whether task performance changed on an individual basis and whether the variability of task performance was associated with coordination variability. The effect of task variability on coordination variability has not previously been explored for cutting manoeuvres and may be interesting to consider in future analyses.

Finally, significant changes were observed in knee ab/adduction and knee internal/external rotation from 98 to 100% and 64 to 82% of stance respectively. The reported repeatability metrics in this and other studies (Table 6.9) demonstrate that the changes observed in knee ab/adduction and internal/external rotation between repeated measurements are large

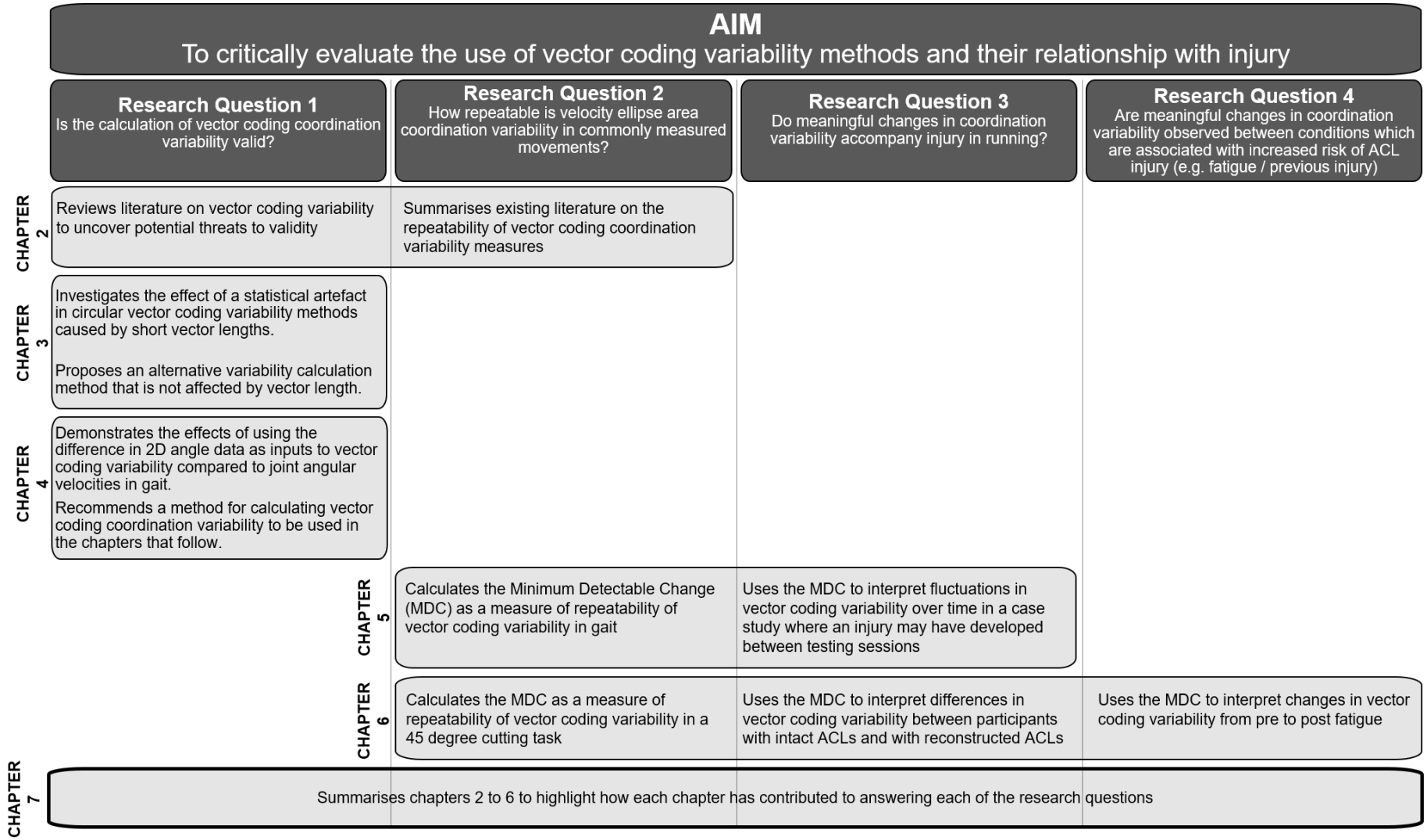
compared to the range of motion of those joints during the stance phase of the cut (approximately 5º for abduction and 15º for internal/external rotation in the repeatability study, Figure 6.17). Knee internal/external rotation has also been observed to have lower relative reliability than other lower limb joint angles during cutting (Alenezi et al., 2016). It is however not known whether the repeatability of mean joint angles is related to the repeatability of variability in their dynamics and how this then impacts the repeatability of coordination variability. The significant changes observed between sessions in the repeatability study were unexpected as the sessions were performed under the same conditions, with an hour's rest in between and markers remained in place between sessions. The periods of significant differences that were observed shed doubt on the credibility of the MDC values for those joint angles during those time periods.

6.5 Conclusion

This chapter has detailed the repeatability (absolute reliability) of coordination variability measured using the velocity ellipse method during the stance phase of a cutting manoeuvre. This is the first example where the repeatability for a coordination variability measure during a change of direction or cutting movement has been reported and can be used by future research in this area to improve research design and the interpretation of results. Similarly, as was found in running gait in Chapter 5.3.4, coordination variability measures were mostly heteroscedastic. The unequal spread of variance in coordination variability affects how researchers should analyse and consider coordination variability measured using the velocity ellipse method in future. The minimum detectable change (MDC) was calculated to measure the repeatability of coordination variability and the MDC ratio was reported for four coordination couplings that detailed the magnitude of percentage change that 95% of percentage changes between two measurements would fall within in the absence of real change. Despite markers remaining in place between data collection sessions and demonstrating that the repeatability of joint angles was similar or improved on those measured elsewhere, the MDC ratios for coordination variability were high compared both to other research and the MDC ratios presented in Chapter 5. This indicated that coordination variability measured using the velocity ellipse method had low absolute repeatability in the cutting movement and practitioners and clinicians may only be able to detect meaningful changes in coordination variability when very large changes occur.

Additional to the repeatability measures reported, this chapter also aimed to understand the effect of fatigue on coordination variability in a group of female team sports players with anterior cruciate ligament reconstructions (ACLR) compared to a group with intact anterior cruciate ligaments (ACLI). This analysis was important to understand whether the findings of

other research related to the effect of fatigue and ACL injury history independently could be replicated. It also added novel information to the literature by testing if an interaction between ACL injury history and fatigue existed. No significant differences were found in average coordination variability measures but statistical tests on coordination variability time series detected two significant differences in coordination variability: knee flexion/extension – knee ab/adduction coordination variability was lower in the ACL reconstructed group from 4 to 6 % of the stance phase. This finding contrasted with other research where higher variability was observed in an ACL reconstructed population and further data would be required to corroborate these results. Hip internal/external rotation – knee internal/external rotation was also found to be lower following fatigue at the very end of the stance phase (96 to 100%) but compared to the MDC the changes observed in individual participants may not have been of a magnitude that exceeded the fluctuations that can be expected between repeated measurements. This was an example where the MDC added additional context to the interpretation of the statistical significance result.


AIM
To critically evaluate the use of vector coding variability methods and their relationship with injury
Research Question 1
Is the calculation of vector coding coordination variability valid?
Research Question 2
How repeatable is velocity ellipse area coordination variability in commonly measured movements?
Research Question 3
Do meaningful changes in coordination variability accompany injury in running?
Research Question 4
Are meaningful changes in coordination variability observed between conditions which are associated with increased risk of ACL injury (e.g. fatigue / previous injury)
CHAPTER 2
Reviews literature on vector coding variability to uncover potential threats to validity
Summarises existing literature on the repeatability of vector coding coordination variability measures
CHAPTER 3
Investigates the effect of a statistical artefact in circular vector coding variability methods caused by short vector lengths.
Proposes an alternative variability calculation method that is not affected by vector length.
CHAPTER 4
Demonstrates the effects of using the difference in 2D angle data as inputs to vector coding variability compared to joint angular velocities in gait.
Recommends a method for calculating vector coding coordination variability to be used in the chapters that follow.
CHAPTER 5
Calculates the Minimum Detectable Change (MDC) as a measure of repeatability of vector coding variability in gait
Uses the MDC to interpret fluctuations in vector coding variability over time in a case study where an injury may have developed between testing sessions
CHAPTER 6
Calculates the MDC as a measure of repeatability of vector coding variability in a 45 degree cutting task
Uses the MDC to interpret differences in vector coding variability between participants with intact ACLs and with reconstructed ACLs
Uses the MDC to interpret changes in vector coding variability from pre to post fatigue
CHAPTER 7
Summarises chapters 2 to 6 to highlight how each chapter has contributed to answering each of the research questions

CHAPTER 7: CONCLUSION

7.1 Introduction

In the literature review it was highlighted that threats to the validity of certain vector coding methods had been speculated about (Heiderscheit, Hamill and van Emmerik, 2002; Mullineaux, 2017), but never investigated. In addition to this, numerous calls had been made for the collection of longitudinal data to better understand the hypothesised links between coordination variability and injury (e.g. Hamill, Palmer and van Emmerik, 2012; Baida et al., 2018). Knowledge of the repeatability of coordination variability measures is important in the interpretation of such data but information about the repeatability of coordination variability methods was also found to be sparse. This thesis therefore aimed to progress this area of research by investigating the validity and repeatability of vector coding coordination variability methods and contributing to the applied area of these measures by investigating within individual and between group changes and differences in coordination variability in response to different conditions (such as injury and fatigue). The following research questions were posed and brief summaries are included below that detail the contributions within this thesis in relation to each research question.

7.2 Executive Summary of Findings

1. **Is the calculation of coordination variability valid?**
    1.1. Coordination variability calculated using circular statistics is affected by an artefact related to the length of the vector joining subsequent time points on the angle – angle plot. The artefact has the potential to cause steep rises that dominate the coordination variability time-series at periods of the movement when vector lengths are short (Chapter 3).
    1.2. A bivariate measure of spread (ellipse area) was demonstrated as a measure of coordination variability that was not affected by the proximity of data points on the angle – angle plot (Chapter 3).
    1.3. The use of angular velocities to calculate ellipse area (a velocity ellipse method, VEM) better adheres to definitions of angular dynamics, retains more temporal information and is more robust to small amounts of noise in the angle signal than methods that use vectors defined by the differences between consecutive joint angle data points (Chapter 4).
2. **How repeatable is ellipse area coordination variability in commonly measured movements?**

2.1. Coordination variability measured using the ellipse area method was mostly heteroscedastic and this is an important feature to consider (Chapter 5 and Chapter 6).

2.2. Minimum detectable change ratios in treadmill running gait ranged from 1.47 to 1.89 in coordination variability averaged across the gait cycle and 1.55 to 4.62 across the time series for the four coordination couplings investigated. This showed that increases of between 47 and 362% or decreases of 32 to 78% would be required within an individual to be suggestive of change greater than that which can be expected due to random fluctuations in coordination variability couplings that are commonly used in the literature. (Chapter 5)

2.3. Minimum detectable change ratios in a 45° side-cutting task ranged from 1.66 to 2.23 in average coordination variability and 1.91 to 7.95 across the time series for the four coordination couplings investigated. This indicated that increases of between 66 and 695% or decreases of 40 to 87% would be required within an individual to be suggestive of change greater than that which can be expected due to random fluctuations, in coordination variability couplings that have been used in published cutting research. (Chapter 6)

3. Do meaningful changes in coordination variability accompany injury in running?

3.1. In the case study example, an individual who presented with heel pain eight weeks after having first attended testing in the lab did not have high or low coordination variability compared to the rest of the group prior to the onset of pain or when pain was present (Chapter 5).

3.2. Coordination variability of the case-study individual did not change by an amount greater than that expected (due to random fluctuations) between data collections where the individual was pain free to the final data collection when running was painful (Chapter 5).

3.3. Combining the observations in points 3.1 & 3.2, there was no evidence to suggest that coordination variability might have played a role in the onset of pain in this individual nor that coordination variability changed as a result of the pain experienced (Chapter 5)

4. Are meaningful changes in coordination variability observed between conditions (i.e. fatigue / previous ACL injury) that are associated with increased risk of ACL injury?

4.1. A significant decrease in hip internal/external rotation – knee internal/external rotation was observed in the final 4% of the cut following the fatigue protocol, but the magnitude of change was only greater than the MDC for two of the twenty participants (Chapter 6).

4.2. The ACLR group had significantly lower knee flexion/extension – knee ab/adduction coordination variability than the ACLI group from 4-6% of stance of the cut (Chapter 6)
4.3. No interactions between ACLI/ACLR group and fatigue were observed (Chapter 6).

7.3 Impact

In Chapter 3, the simulated data clearly showed that vector coding coordination variability measures based on circular statistics were affected by a statistical artefact and provided strong evidence to support that experimental coordination variability data in running can be impacted by this artefact. The artefact can cause pronounced peaks that dominate the calculated coordination variability at times when the vectors between points on the angle – angle plot are very short. These peaks likely detract from finer changes in coordination variability that occurred elsewhere in the movement cycle. The findings of Chapter 3 were published in 2018 and their effects can be observed in the literature: a recent publication that used circular statistics in vector coding variability calculations also calculated vector length component of the dominant segment (there referred to as range of motion) (Needham et al., 2020). The authors reference the artefact as a possible factor in the increase in coordination variability observed when participants transitioned between in and anti-phase coordination patterns and the results they present are similar to those presented in Chapter 3 in that periods of high coordination variability coincided with periods of the gait cycle where the vector component of the dominant segment was shorter. Other studies have chosen to transition away from circular methods and have either used the ellipse area method proposed in Chapter 3 (difference ellipse method) (Bonacci et al., 2018; Foch and Milner, 2019), the velocity ellipse method (Bonacci et al., 2020) or alternative bivariate measures of vector coding coordination variability (Mulloy et al., 2019). Thus, the research presented has resulted in changes in research practice. It is hoped that researchers that continue to use circular statistics in vector coding calculations will calculate and consider vector length in the interpretation of their data so that the presence of the artefact does not lead to incorrect conclusions being drawn from the data. For those researchers that have opted to use bivariate methods it is hoped that the use of measures of coordination variability that are not affected by the proximity of data points may be more effective at detecting meaningful changes. Chapter 3 highlighted that the steep rises in coordination variability which occurred at the same time as vector lengths were short might have masked more subtle changes in variability at other time points in the gait cycle.

Chapter 4 provided an in-depth discussion about the way in which traditional vector coding methods have represented angular dynamics. The discussion highlighted that the techniques originally used to represent angular dynamics that calculated the change in joint angles

between data points sampled from temporally normalised signals did not align with conventions within biomechanics of representing angular dynamics where angular velocities are used. Until 2019 all measures of vector coding coordination and its variability have used the traditional calculations but in some instances these results can be unrepresentative of the true angular dynamics. For example, in Chapter 4 it was demonstrated that when the traditional representation and the angular velocity alternative were used to calculate coordination variability on the same running gait dataset, couplings that contained knee ab/adduction, knee internal/external rotation or hip ab/adduction components were least similar. This was likely because the representation of movement dynamics using the change in an angle in one axis does not consider movement that occurs about the other two axes. This has implications for researchers or clinicians measuring coordination variability who can only measure two-dimensional movement as some couplings may be less accurate representations of the true angular dynamics than others. The couplings most likely to be problematic in gait have been highlighted above and within Chapter 4 but research wishing to use two-dimensional motion capture for other movements should endeavour to understand which couplings may be least similar to their angular velocity equivalents. The reasons suggested for differences between the traditional calculations and the angular velocity components was due to contributions from other axes of rotation and the different handling of temporal information between methods. A lack of temporal information in vector coding has previously been viewed as a disadvantage of the vector coding method therefore the proposal to use angular velocities offers a simple solution to this issue for vector coding measures of coordination and coordination variability that has already been adopted by other authors (Bonacci et al., 2020; Hall et al., 2020).

In addition to the impact of Chapter 3 and 4 and their corresponding publications on the methods used to calculate coordination variability, this thesis has now also provided information on the repeatability of the proposed velocity ellipse area measure in running (Chapter 5) and a 45 degree cutting task (Chapter 6). This information can be used to improve the quality of interpretations that can be made from coordination variability data in the future by indicating what magnitudes of change can be expected within individuals between repeated data collections with no intervention. The benefit of these values was demonstrated within this thesis where the repeatability measures were used to interpret individual changes in coordination variability with the presence of heel pain in running, and in cutting after a fatiguing protocol.

Further to this, Chapter 5 provided one of the first examples of longitudinal coordination variability data in an individual who transitioned from an asymptomatic to symptomatic state between data collection sessions. In this case study example, the evidence did not support the coordination variability – injury hypothesis. Whilst a sample of one is too small to inform any

widespread conclusions it is an important first step towards understanding whether the hypothesis has practical meaning. In the very specific case study within this thesis, coordination variability did not appear to have played a role. The impacts of this should be to encourage researchers investing their efforts in cross sectional studies to divert their attentions to testing the hypothesis using longitudinal data. Without prospective evidence to support the hypothesis many of the justifications for conducting cross-sectional studies no longer hold. The repeatability metrics within chapter 5 will be useful for the interpretation of such data.

In chapter 6, participants were observed to be less variable in the hip internal/external rotation – knee internal/external rotation coupling at the very end of stance (the final 4%) after fatigue and the ACLR group had lower knee flexion/extension – knee ab/adduction coordination variability than the ACLI group in a 45° side-cutting task between 4 and 6% of the stance phase. These findings did not support the only published example of similar research where variability was found to be higher in an ACL reconstructed population compared to a healthy group (Pollard et al., 2015). Therefore, further research will be required to confirm the presence of a relationship and then look to understand its relevance to ACL injury via prospective research.

7.4 Limitations

Within this thesis a method was proposed for calculating coordination variability based on ellipse area calculation. The method was demonstrated by calculating the repeatability of and changes in the velocity ellipse area during two different movements: running and cutting. In the analysis of these data, several observations were made related to possible limitations of: the ellipse method, its repeatability and the data that was collected. Each of these factors is discussed in turn below and recommendations for solutions and future research are proposed.

7.4.1 Methods

Number of trials

The importance of the number of trials used in the calculation of coordination variability and explanation for this can be demonstrated simply in simulated data with a univariate measure of standard deviation, where the standard deviation is calculated from a spectrum of sample sizes drawn from a normally distributed population of 10,000 points with a mean of 100 and standard deviation of 25 (Figure 7.1). With lower sample sizes, the standard deviation frequently take values that are unrepresentative of the population but as sample size increases, the standard deviation more consistently represents its true value (Figure 7.1A). The same concepts apply to simulated bivariate data with ellipse area as a measure of variability (Figure 7.1B). These examples are based on normally distributed simulated data (with covariance

matrix $\begin{bmatrix} 25 & 0 \\ 0 & 25 \end{bmatrix}$) which may not represent the distributions of all possible experimental data sets but the concept that is demonstrated remains the same. The 5th and 95th percentiles (and the distribution of data between them) indicate the range of possible values can be very high with low sample sizes. Together these demonstrate that the reliability of the standard deviation or ellipse area is compromised at smaller sample sizes and is a plausible explanation for the low repeatability observed for both running and cutting movements in this thesis. Examples in the literature include as few as 3 movement repetitions (e.g. Davis et al., 2019) and as many as 15 (e.g. Heiderscheit, Hamill and van Emmerik, 2002; Herb, Chinn and Hertel, 2016; Herb et al., 2020). Specifically, for the ellipse used in the CI2 Method, upon which the ellipse calculations in this programme of research are based, Mullineaux (2017) recommended no fewer than 10 trials for the CI2 method based on simulations performed by Jackson et al. (2011). The limitation of the number of trials is therefore pertinent across all vector coding research relating coordination variability and injury to date. In this thesis specifically, twenty and ten trials were used in the running and cutting data collections respectively: these values meet or exceed the recommended minimum number and represent a high number of trials compared to research using the same movements, but repeatability may have been improved had a greater number of trials been used.

A further observation in both univariate and bivariate cases, is that the median line demonstrates an underestimation bias when calculated from lower sample sizes (Figure 7.1, in bivariate cases similar results have also been reported by Jackson et al. (2011). Whilst this would be problematic for comparing data from different studies using different numbers of movement repetitions it is not important for the interpretation of the results within this thesis where the same number of trials were used for individuals within each chapter and the movement with the lesser number of trials (cutting) recorded greater ellipse areas despite the underestimation bias. Jackson et al. (2011) presents a possible solution to this by reducing the degrees of freedom in the covariance matrix calculation that may be worth further exploration. Additional work will be important to determine how many trials are required so that researchers can be more confident that the number of trials they use is not compromising the accuracy and repeatability of their measurements. The results of such analyses may limit the range of applications of coordination variability as a measure though, as task and situational demands in sporting movements can mean it is not always possible to collect high trial numbers.

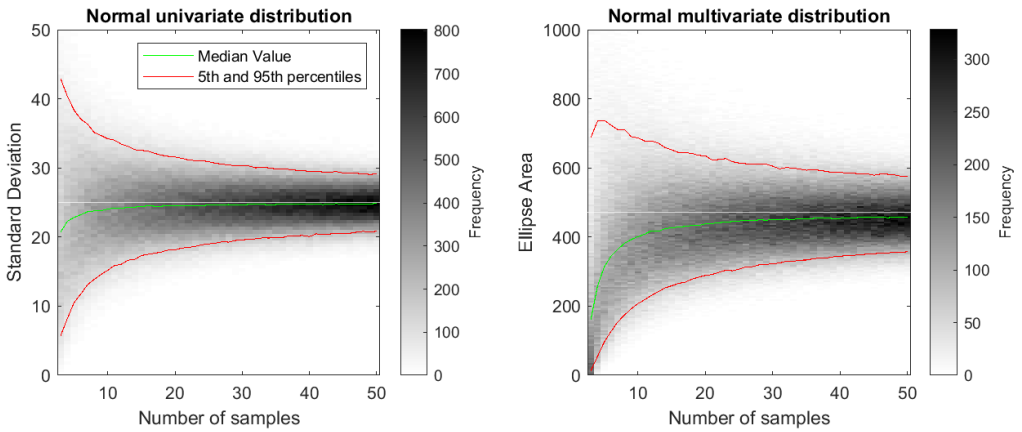


Figure 7.1. Demonstration of how the number of samples (i.e. number of movement repetitions) can impact on univariate (standard deviation) and bivariate (ellipse area) measures of spread. A) A data set of 10,000 points were randomly selected from a normal distribution with mean 100, standard deviation of 25 (MATLAB function 'normrnd'). 10,000 iterations were then performed, where n data points (i.e. number of samples ranging from 3 to 50) were randomly sampled (MATLAB function 'datasample') from the data set and used to calculate a sample standard deviation. The 10,000 standard deviations calculated for each number of samples formed a distribution which is represented by the grey colour scale. B) A data set of 10,000 vectors were randomly selected from a multivariate normal distribution with means [100,100] and covariance matrix $\begin{bmatrix} 25 & 0 \\ 0 & 25 \end{bmatrix}$ (MATLAB function 'mvnrnd'). 10,000 iterations were then performed, where n data points (i.e. number of samples ranging from 3 to 50) were randomly sampled (MATLAB function 'datasample') from the data set and used to calculate a sample ellipse area using the same calculation methods demonstrated in chapter 5 and 6. The 10,000 ellipse areas calculated for each number of samples formed a distribution which is represented by the grey colour scale. In both plots, the white horizontal line represents the true distribution of the population, the green line represents the median standard deviation of the distribution for each number of samples (i.e. movement repetitions) and the red lines represent the 5th and 95th percentiles.

Outliers and the ellipse area calculation

In chapter 4 and 6 specific examples were provided of ellipses where the size and therefore area of the ellipse appeared to have been inflated because of outliers. Here the term outliers is used to describe individual points which lay outside the overall pattern of a distribution (Moore, 2017). Outliers were often not present for the entire duration of the movement, nor were they present in all individuals, but they were observed on a number of occasions and were particularly prevalent in the cutting data. The data had been checked visually for measurement errors therefore outliers were assumed to result from biological variation in the completion of the task.

The presence of outliers may have affected the conclusions drawn in this thesis in the following ways:

1. Coordination variability was being measured in this context as a potential indicator of injury risk. In their very essence, variability measures should take outliers into account as long as those outliers are a result of biological variation (i.e. not the result of measurement error). Therefore, the important question in the case of variability is how much of an influence one or multiple outliers (or indeed different distributions of data

points) have on the coordination variability measure. In the case of the variability – injury hypothesis, it is then important to understand whether this influence is proportional to the effect on injury risk. Unfortunately, as was highlighted in Chapter 2, we do not yet fully understand the exact responses to repetitive (low variability) or highly variable loading in biological tissues that may lead to chronic injury or the degradation in strength of a structure such as the ACL. Nor do we understand how coordination variability measures translate to the distribution of loading of each of these structures. In chapters 3 and 4 the velocity ellipse area was proposed as a more valid measure of coordination variability as it was not affected by the proximity of data points on the angle – angle plot but it is difficult to comment whether the changes in ellipse area that are observed due to outliers are disproportionate or appropriate. The changes in ellipse area that occur as a result of outliers are complicated and depend on the position and number of outliers compared to the distribution of the other data points. In a rudimentary example using real data and applying a manipulation to one or two of the data points, it can be seen that for the ellipse shown in Figure 7.2A, the ellipse area can be 1.7 times larger if a single data point is moved 100 $^{o}\cdot s^{-1}$ from a position close to the ellipse centroid along the secondary ellipse axis (Figure 7.2B and Figure 7.3B), and 2 times greater when this process is applied to two data points (Figure 7.2C and Figure 7.3B).

2. In chapters 5 and 6 the repeatability of coordination variability measures was determined by measuring coordination variability across multiple trials (in the case of this thesis, 20 gait cycles or 10 cutting movements) on two occasions. The effect of outliers does not affect the repeatability in this context if the data measured has a similar contribution of outliers in one session as it did in the second. However, if the occurrence of outliers is small in comparison to the number of trials collected and in one session, no outliers are recorded, but in the next session, one occurs, then this will negatively impact the repeatability of the ellipse area measurement.
3. Finally, in chapters 5 and 6 this thesis looked to understand whether intra-individual changes occurred either over time or as a result of fatigue. The ability to detect meaningful change and significant differences is affected by the repeatability of the data therefore the factors described directly above in point 2 may have therefore also impacted conclusions related to intraindividual changes.

There are a number of approaches that have the potential to reduce the effect or presence of outliers in the calculation of coordination variability. Calculating variability from a greater number of trials would mean that each individual datapoint had less effect on the ellipse in addition to the benefits in accuracy and reliability (as discussed above, page 213). Similarly,

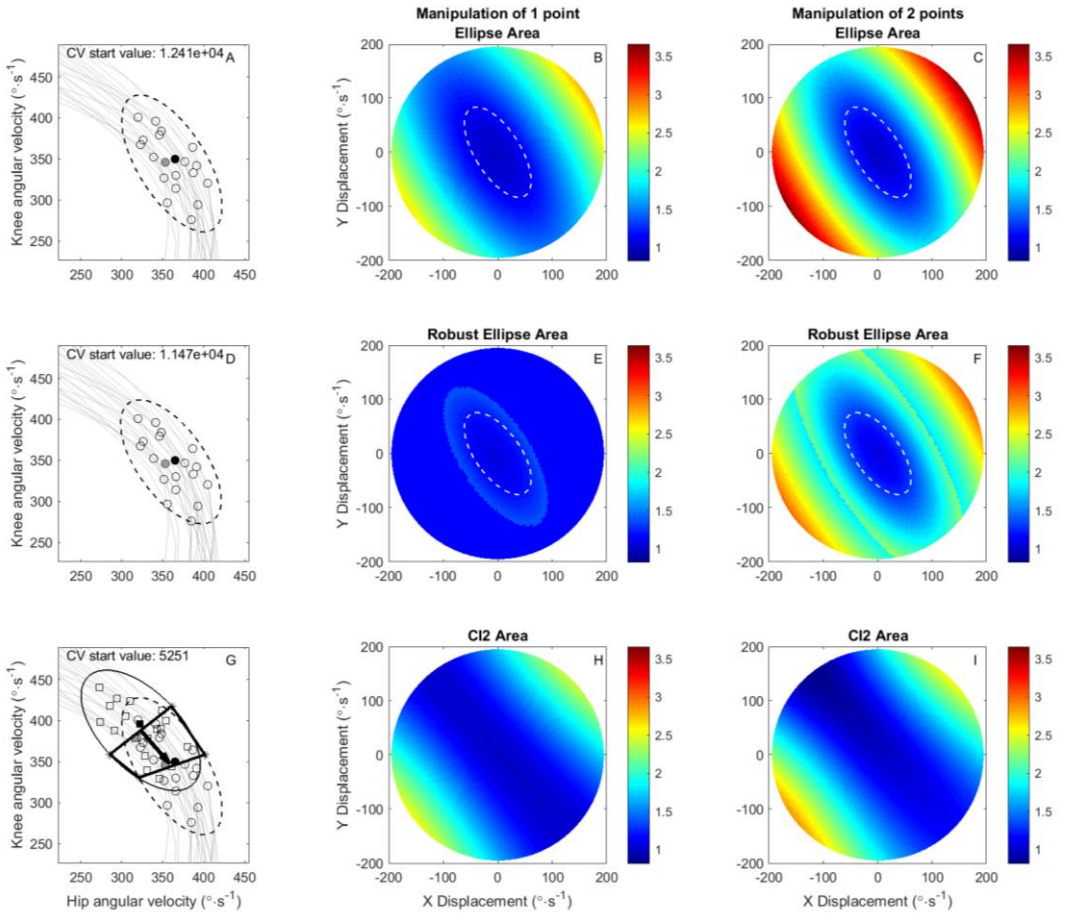


Figure 7.2. Simulated effect of outliers for three bivariate coordination variability methods. The same sample data as was used in examples in the literature review has been shown here for one participant at 60% of the gait cycle for coordination variability of hip flexion/extension – knee flexion/extension coupling using angular velocity inputs. The first column demonstrates the original data and the method used in the respective row. Data points from two of the twenty gait cycles that were situated closest to the centre of the ellipse are highlighted in black and grey and the coordination variability area calculated for each method is reported in the top left-hand corner (units: $^{o2}\cdot s^{-2}$). The middle column demonstrates the ratio of changes in coordination variability area compared to the areas reported in columns when a single outlier (the black data points highlighted in A, D and G) was translated from its original position by a given radius and angle. E.g. 1 on the colour scale represents no change, but 2 represents twice the coordination variability of the original data set shown in the left column. The right column demonstrates the ratio of changes in coordination variability area compared to the 'start value' areas reported in A D and G when two outliers (the black and grey data points highlighted in A, D and G) were translated from their original position by a given radius and angle. The top row uses the method which has been used throughout this thesis (ellipse area method). The middle row uses mcdcov (Verboven and Hubert, 2005) to calculate a robust ellipse (settings all points are considered by making alpha 1) where the area of this could be used as a measure of coordination variability. The third row uses the CI2 area (Mulloy et al., 2019) whereby the area of the highlighted convex quadrilateral represents coordination variability from 59 to 60% of the gait cycle. In this instance the translation was applied to the data at both time points (the highlighted squares and circles in G).

the influence of individual points could also be modified via weighting, though this has not been attempted in the area of sports biomechanics to date. A number of other fields have explored robust ellipse estimators (e.g. Daszykowski et al., 2007; Filzmoser and Todorov, 2013; Maronna and Yohai, 2017; Leys et al., 2018; Rousseeuw and Hubert, 2018). Many of

the methods discussed reduce the effect of outliers on the ellipse formation, an example of which is presented in the middle row of Figure 7.2, where outliers have a lesser effect on the calculated area in the robust ellipse example provided compared to the ellipse area used in this programme of research. However, it is also clear that there is a range outside of which the outlier no longer influences the ellipse area calculation causing unpredictable jumps in ellipse area measurements (Figure 7.3). Further work would be needed to determine whether such methods were beneficial both for the repeatability and validity of coordination variability measures.

Furthermore, alternative measures of coordination variability should also be considered. The CI2 area differs to the ellipse method in that a convex quadrilateral is formed from points defined by two consecutive ellipses (Mulloy et al., 2019). CI2 area increased by of 59% for one outlying data point, and 79% for two along the radius where the greatest increases were observed (Figure 7.2G, H & I, Figure 7.3). This demonstrated a less exaggerated response to the presence of outliers compared to the ellipse area method but a marked response, nonetheless. Along the axis perpendicular to the axis of maximum change, the CI2 area was much less responsive to the outliers, showing almost no change (<1%) when one data point was displaced by 100 $^{o}\cdot s^{-1}$ and a decrease of 9% when the displacement was applied to two data points. These results are promising but it should be considered that the response may be specific to the scenarios presented in the simulation. Further work would be required to understand the complex responses that may occur in portions of the curve where the ellipse underwent greater change in its orientation between data points and when the translation applied to outliers is not consistent from one time point to another. The total variability measured using this method may also be related to the length of the vector connecting the two ellipses (a similar concept to that discussed in Chapter 3) therefore users should consider this when interpreting coordination variability measured using this technique.

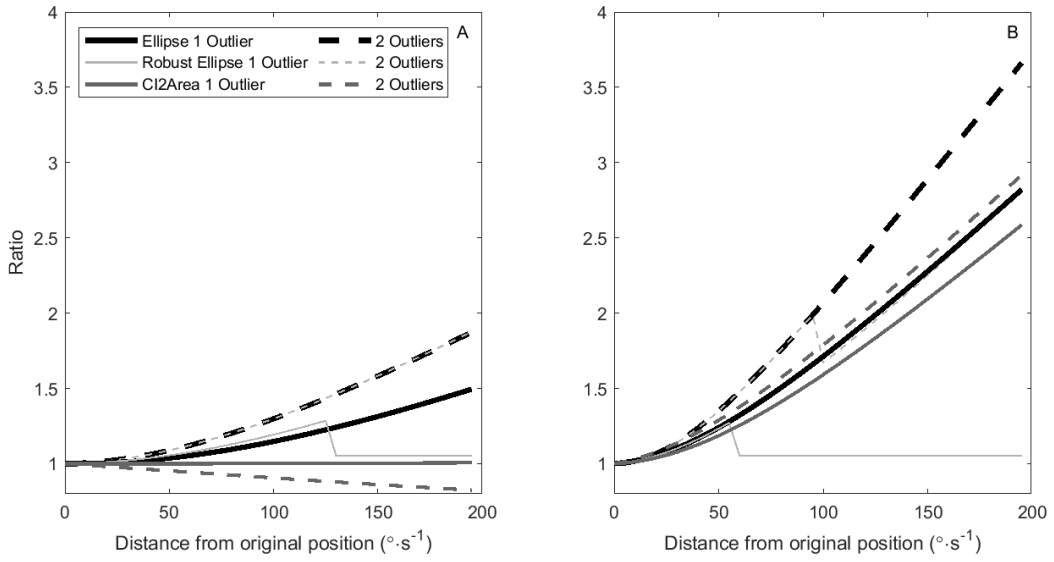


Figure 7.3. An alternative depiction of the effect of outliers on three measures of coordination variability. The ratio of change that occurred in coordination variability from the original area (i.e. the areas displayed in Figure 7.2 A, G and E) when one (solid lines) or two (dashed lines) of the points in the ellipse were translated away from their original positions by a given distance. Three coordination variability methods are demonstrated: the ellipse area method used in this thesis (black, wide), the robust ellipse area method (mcdcov with α set to 1, Verboven and Hubert (2005), light grey, thin) and the CI2Area (Mulloy et al. (2019), mid grey). A) Represents the radius of the circle from Figure 7.2 in which the greatest change in area occurred for each measure B) represents the radius perpendicular to that shown in A.

Repeatability calculations

In this thesis, a repeatability 'coefficient' metric (referred to as the minimum detectable change, MDC) was calculated for average coordination variability across the movement and coordination variability and average joint angle time series data. The MDC represented a range within which 95% of the differences between two repeated sessions should fall. This and similar metrics help people who have collected data on the same measure to put the magnitude of change they observe into context. Observed changes can be compared to the repeatability coefficient to understand if the change was greater than was observed between two sessions where no meaningful change would be expected. The ability to make this comparison is very useful if it is not possible to collect many samples from individuals. This is particularly relevant for coordination variability as the nature of the measure itself computes one output from multiple trials. However, there are several factors that need to be considered in their use:

The repeatability calculations are not statistical tests and therefore cannot be used for inference. In addition to this, the boundaries that it sets are based upon the probability that 95% of differences between a pair of observations is less than the MDC. Some researchers argue that these boundaries are too stringent and could lead to effects going unrecognised that have a high likelihood of being meaningful (Hopkins, 2000). It is challenging to judge what value of certainty is appropriate without knowledge of what a meaningful change in

coordination variability might be for injury or other purposes. It is also recommended that when multiple tests of this kind are performed, one should consider that the likelihood of exceeding the repeatability statistic would increase with the number of tests performed. The origins of the repeatability coefficient are based on single value measures and they were not designed to be applied to time series data. By applying the same calculations to every time point (in Chapter 5 this was 101 times, in Chapter 6, 51 times) and to every variable, the total number of comparisons becomes large and the likelihood of false positives is increased. Other methods exist but a review into the topic comparing a range of methods (namely, pointwise comparisons, functional limits of agreement, coefficient of multiple correlation, distance measures and similarity measures) suggested that pointwise comparisons were the best option (Pini, Markstrom and Schelin, 2019). The results of this thesis have provided valuable insights into the repeatability of coordination variability measures that will be useful to researchers planning to measure coordination variability in the future using common techniques from the field of research. Given the rise in popularity of time series data (e.g. Pataky, Robinson and Vanrenterghem, 2013; Warmenhoven et al., 2018), further research to determine the best methods to report and use repeatability estimates in an easy way for both homo and heteroscedastic data will be important.

7.4.2 Sample Sizes

In this thesis, there were four sample sizes to consider. In the repeatability of coordination variability in gait, twenty participants attended testing in the lab on three occasions that were unequally spaced to answer questions related to within and between day repeatability. In the investigation of coordination variability repeatability in cutting, ten participants repeated the same data collection session twice within the space of an hour. Sample sizes of a minimum of 20 but preferably closer to 50 have been recommended for investigating repeatability (Atkinson and Nevill, 2001). Thus, chapter 5 met the recommended minimum requirement, but chapter 6 did not. Both repeatability studies would have benefitted from a greater number of participants but were restricted in the ability to recruit local participants that met the inclusion criteria of each study to volunteer their time. The low participant numbers, in chapter 6 particularly, increased the likelihood of sampling error and could have resulted in MDCs that were less representative of the population than if a greater sample had been used. Nonetheless the MDCs presented provide valuable information for the interpretation of vector coding coordination variability, where there is very little information on how repeatable these measures are.

Prospective data relating to injuries is notoriously difficult to collect and requires large sample sizes as it cannot be guaranteed that injuries will occur. In this instance one participant was

enough to provide initial descriptive evidence and demonstrate the use of the MDC values, but to draw any conclusions future research will need to systematically monitor a large number of people to understand whether coordination variability is related to the onset of injury in general, or any specific injuries.

Finally, the sample size for the between – within measures design used in the fatigue study would normally be calculated prior to the study taking place based on an estimated effect size from previous experimental findings. Because chapter 6 was the first study to use the ellipse area method in this context it was not possible to estimate a required sample size based on population estimates for effect size and standard deviation before the study took place. It was decided that ten participants would be recruited in each group given that the number of female athletes competing in team sports at a good to high level is limited and the number that have also had ACL reconstructions is much smaller again. When more data is available to estimate population variance and effect sizes, it may become apparent that more participants are needed to address similar questions, in which case it may be necessary to form collaborations with clinics and other universities to recruit a greater number of participants. The challenges in defining these population parameters and recruiting large numbers of participants further strengthens the use of a more individual and descriptive approach by comparing changes and differences to the MDC.

7.5 Recommendations

Chapter 2 summarised the literature on vector coding coordination variability and its association with injury and identified several important areas that require further work to advance the field. Some of these areas have been addressed within this thesis, and in some instances the process of addressing these questions highlighted the emergence of new questions. In other instances, there were questions which were not within the scope of this thesis. Taking both into consideration the following recommendations are proposed as the most important aspects to address in future research about coordination variability and its association with injury.

In Chapters 3 and 4, methodological issues related to a statistical artefact and the representation of angular dynamics in traditional methods of calculating vector coding coordination variability were addressed. Across the same chapters, a new method was proposed for the calculation of coordination variability, which was termed the velocity ellipse method (VEM). In Chapters 5 and 6, work was undertaken to understand how repeatable the VEM was. Across both chapters, repeatability was deemed as low and this was identified as a barrier to understanding what change in coordination variability could be meaningful. The

possible benefits of such an understanding are not only relevant for understanding the link between coordination variability and injury, but across all applications of coordination variability measures (i.e. also in health, learning or expertise). In this chapter, possible limitations of data collection and analysis protocols that are common to coordination variability research studies have been identified: low numbers of movement repetitions may increase the likelihood of high variation due to sampling and rudimentary simulations have shown that outliers may exert disproportionate effects on the calculation of coordination variability using the VEM (Figure 7.2). Future work in this area would benefit from demonstrating a method of calculating coordination variability that is both repeatable and sensitive enough to detect meaningful change. It is proposed that investigating the use of an increased number of movement cycles and exploring the benefits and limitations of different methods for calculating bivariate spread (some of which have been shown as examples in Figure 7.2) may be most fruitful before additional research is conducted to use the measure.

Further to this, the hypothesis associating coordination variability and injury are based upon a repetitive loading hypothesis. To best apply the coordination variability measure future research should look to combine research from different specialisations such as training load and biomechanical and biological/physiological modelling. The addition of training load information would add context to longitudinal monitoring. Coordination variability measures can quantify how varied loading is between repeated cycles, but the number of repeated cycles that occur in total is an important moderating factor when considering injury. Modelling techniques that quantify the forces that are experienced by individual biological structures, how variability in joint angles across multiple movement cycles is associated with the distribution of loading in those structures and how those biological structures remodel in response to those loads would all be valuable in better understanding the exact mechanisms behind the hypothesised association between coordination variability measures and injury.

7.5.1 Recommendations summary

Thus, the following steps are recommended to better understand the utility of the velocity ellipse measure:

- Determine number of movement repetitions required for improved repeatability of the measure in gait where greater repeatability was observed
- Concurrently investigate an approach to manage non-normal bivariate distribution of the points in the ellipse (whether due to outliers or underlying distribution of the data)
- Retest the repeatability of the measure using the refined methodology

Once these factors have been determined and the repeatability of the measure is improved, the refined method and the information about its repeatability can be applied to investigate applied questions. The following steps are recommended:

- Use musculoskeletal modelling to understand which coordination couplings are relevant for specific injuries and how joint position and coordination variability may interact to load biological structures in a way that may result in injury.
- Use this information with the refined velocity ellipse area method to track individuals' coordination and coordination variability in targeted segment or joint couplings longitudinally to understand what changes occur over time and why (e.g. injury). Training load should be measured as a possible moderating factor.

7.6 Conclusion

This programme of research has provided a novel perspective on vector coding coordination variability methods. Within this thesis, the existence of a statistical artefact related to the traditional use of circular statistics was demonstrated, the benefits of using alternative calculation approaches based on angular velocities was presented and from these, an alternative method for calculating coordination variability was proposed (the Velocity Ellipse Method, VEM). Two further studies were conducted to understand the repeatability of the VEM and its ability to detect change within individuals and between groups in two different movements (running and cutting) over different timescales (e.g. an acute fatiguing intervention in cutting compared to a two month monitoring period for the running data). These studies measured coordination variability under repeated conditions and calculated the 'minimum detectable change' within which 95% of the differences between two sessions, conducted under the same conditions, should fall. In a longitudinal case study investigation, an athlete transitioned from a healthy running state to one where they experienced heel pain. No changes were observed in coordination variability that were greater than the within and between day MDC, or that stood out as different to the three previous data collections from the same individual. The participant also did not demonstrate coordination variability that was high or low compared to the rest of the population. This is one of few longitudinal investigations into coordination variability and injury and in this instance, did not provide evidence to support an association between them. In a repeated-measures, two group design, the effect of fatigue, previous ACL reconstruction and the interaction between fatigue and previous ACL reconstruction was investigated. Knee flexion/extension – knee ab/adduction coordination variability was lower in the ACL reconstructed group from 4 to 6 % of the stance phase than in the control group. This finding contrasted with other research where higher variability was observed in an ACL reconstructed population and further data would be

required to corroborate these results. Hip internal/external rotation – knee internal/external rotation was also found to be lower following fatigue at the very end of the stance phase (96 to 100%). Whilst a group significant difference was observed, only two participants showed changes greater than the MDC. The combined investigations of repeatability and applied questions related to coordination and variability suggest that the repeatability of the VEM may be too low to detect methodologically meaningful changes. Possible causes, such as the number of trials used and the weighting of outliers, have been presented and discussed. Finally, suggestions for further work have made that may improve the detection of meaningful differences in future coordination variability research.

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